Exhibit 6

DAMAGED DAMAGES: ERRORS IN PATENT AND FALSE ADVERTISING LITIGATION

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Patent and false advertising damage awards are in disarray. Courts are imposing astronomically inflated awards that overcompensate companies for the infringement or deceptive practices. The culprit is the Choice Based Conjoint method—a survey based statistical method which seeks to estimate how much consumers value individual features of a product. Originally coming from marketing scholarship, this methodology has been become the prevailing method federal courts use to calculate damages in these cases. And it is being consistently misused.

This article is the first to highlight this misapplication and use empirical methodology to explain why the method leads to exaggerated damage awards. The problem is that courts—when deploying this methodology—mistakenly only include patented (false advertised) features in the survey design and neglect to add other key non-patented features. This creates the impression that products are only made up of their patented elements, which naturally overestimates the value of these elements. Doctrinally, patent damages seek to compensate parties only for the value of the patented feature as opposed to the full product. This article realigns this statistical method so that all relevant features are included within the survey model and courts are better equipped to impose more precise awards that actually compensate for the infringement and false advertisement.

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INTRODUCTION

Damage awards in patent and false advertising cases are in disarray. In many cases these awards have been astronomically inflated. In both patent infringement and false advertising lawsuits, setting the damage award is a critical step in litigation. For patent infringement cases, if plaintiffs cannot prove more than nominal damages, there is really no point to bring a lawsuit.[3]

[3] Section 289 of the Patent Act provides that damages need be proved in the infringement context. A person who manufactures or sells "any article of manufacture to which [a patented] design or colorable imitation has been applied shall be liable to the owner to the extent of his total profit." 35 U. S. C. §289. *See also* Dobson v. Hartford Carpet Co., 114 U. S. 439, 444 (1885) (holding that a "plaintiff must show what profits or damages are attributable to the use of the infringing design.") The Patent Act of 1952 reinforces the importance of damages to any successful patent infringement suit. (35 U.S.C. §289. 66 Stat. 813). *See also* Section 284 of the Patent Act which defines the scope of patent damages. Although one can get a ruling of infringement, without a showing of damages flowing directly from the infringement, there is no monetary remedy. For a case that found infringement but no damages, hence canceling a jury trial *see* Apple, Inc. v. Motorola, Inc., No. 1:11-cv-8540, 2012 WL 1959560 (N.D. Ill. May 22, 2012). There Judge Posner held

Similarly, with false advertising, the only way for a class to be certified is for the plaintiffs to show that damages can be accurately measured on a class wide basis.[4] Without this determination, the cause of action is effectively dead on arrival.

Most simply, damage awards seek to compensate plaintiffs for only the specific value of a patented (falsely advertised) feature of a product that is otherwise made up of many other features. For example, if a litigant infringes on the patented spell check of Microsoft Word, damages are awarded only for the value of spell check, not the full value of Microsoft Word. Measuring this specific value, however, is a difficult task.[5] As such, experts (economists, marketers, accountants, social scientists) are often called into court to assist a jury or a judge in the process of valuing these features. These experts employ sophisticated empirical methodologies to come up with their valuations.[6]

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there that although there was an infringement under 35 U.S.C. 271, no damages could be proved and hence the case was moot. *See also* infra Section 1.

[4] *See* Comcast Corp. V. Behrend*,* 133 S. Ct. 1426, (2013) (holding that plaintiffs must offer evidence of common damages at the certification stage). Rule 23b(3) of the Federal Rules of Civil Procedure creates a requirement that damages must be proved on a class wide bases. Fed. R. Civ. Rules 23(b)(3). For cases denying cert based upon a lack of proof of cognizable *see* Rahman v. Mott's LLP, 13-cv-03482, 2014 BL 339845 (N.D. Cal. Dec. 3, 2014); Dailey v Groupon*,* Inc., No. 11 C 05685, 2014 BL 237928 (N.D. Ill. Aug. 27. 2014); and Daniel F. v. Blue Sheild of Cal., No. 4:09-cv-02037, 2014 BL 225584 (N.D. Cal. Aug. 11, 2014). *See also* infra Section 1.

[5] Kip Viscusi, *The Challenge of Punitive Damages Mathematics*, 30 J. LEGAL STUD. 2, 313 (2001) (discussion the difficulty in setting an appropriate punitive damage amount in order to correctly deter action); R.F. Lanzillotti & A.K. Esquible, *Measuring Damages in Commercial Litigation: Present Value of Lost Opportunities*, 5 J. OF ACC., AUD. & FINANCE 125, (1990) (laying out the complicated task of estimating lost opportunity damages); Kenneth Cole & James Laurence, *How Accurate are Estimates of Aggregate Damages in Securities Fraud Cases?*, 49 BUS. LAW. 2, 505, (1994) (articulating the use of computer simulated techniques to estimate damages).

[6] Shankar Iyer, *Patent Damages in the Wake of* Uniloc v. Microsoft, 23 INTELL. PROP. LITIG. 9, 12–13 (2012). (discussing the use of survey methods to apportion patent damages) There have been many cases in which experts have used complicated methodology to estimate damages in patent and false advertising cases, we list just a few here: TV Interactive Data Corp. v. Sony Corp., 929 F. Supp. 2d 1006, 1020 (N.D. Cal. 2013) (using choice based conjoint analysis to determine patent damages), Apple Inc. v. Samsung Electronics Co., 920 F. Supp. 2d 1079, 1089 (N.D. Cal. 2013*)* (using choice based conjoint analysis to determine patent damages*);* In re: Dial Complete Marketing MDL Case No. 11-md-2263-SM and Sales Practices Litigation (March 27, 2017) (using choice based conjoint analysis to certify a class by showing that all consumers were hurt by Dial's false label claim); Briseno v ConAgra Foods Inc., 90 F. Supp. 3d 919, 2015 BL 54967 (C.D. Cal. Feb. 23, 2015) (using choice based conjoint analysis to certify a class by showing that all consumers were hurt by ConAgra's false claim).

The prevailing methodology to estimate damages in federal patent[7] and false advertising[8] cases is *Choice Based Conjoint* ("CBC"),[9] a survey based statistical method. The problem is the method is consistently being misapplied. In addition, more often than not, judges, juries, and lawyers are not equipped to critically police how experts use and misuse the method.

This article seeks to open the proverbial black box of CBC[10] and argue that its *misuse* in patent and false advertising litigation is drastically inflating damage awards. Ultimately, we argue that billions of dollars of damages have been inappropriately awarded, because the application of the CBC method supporting them has been wrong.

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[7] The following is a non-exhaustive list of patent cases that have used the CBC method to estimate damages: Apple Inc. v. Samsung Electronics Co., 920 F. Supp. 2d 1079, 1089 (N.D. Cal. 2013); TV Interactive Data Corp. v. Sony Corp., 929 F.Supp.2d 1006, (N.D. Cal. 2013); Visteon Global Technologies, Inc. v. Garmin International, Inc., 2016 WL 5956325, (E.D. Mich. 2016); Oracle America, Inc. v. Google Inc., 2012 WL 850705, (N.D. Cal. 2012); Glyenn v. Hyundai Motor America, 2016 WL 3621280, (C.D. Cal. 2016); Seven Networks, LLC v. Google, LLC, 315 F.Supp.3d 933, (E. D. Texas 2018); Simpleair Inc., v. Google, LLC, 884 F.3d 1160, (Fed. Cir. 2018).

[8] The following is a non-exhaustive list of false advertising cases that have used the CBC method to estimate damages: Kurtz v. Kimberly–Clark Corporation, 321 F.R.D. 482 (E.D. N.Y 2017); In re Scotts EZ Seed Litigation, 304 F.R.D. 397, (S.D.N.Y 2015); In re Con Agra, 90 F.Supp.3d 919, (C.D. Cal. 2015); Haldey v. Kellog Sales Company, 324 F.Supp.3d 1084, (N.D. Cal. 2018); In re NJOY, Inc. Consumer Class Action Litigation, 120 F.Supp.3d 1050, (C.D. Cal. 2015); In re Dial Complete Marketing and Sales Practices Litigation, 320 F.R.D. 326, (D. N.H. 2017); Townsend v. Monster Beverage Corporation, 303 F.Supp.3d 1010, (C.D. Cal. 2018).

[9] *See* Greg Allenby, Jeff Brazell, John Howell, and Peter Rossi, *Valuation of Patented Product Features*, 57 J. LAW AND ECON. 3 (2014) (arguing that conjoint analysis has been applied in patent damage calculations widely but has not taking into consideration market competition) and Gregory Sidak and Jeremy Skog, *Using Conjoint Analysis to Apportion Patent Damages*, 25 FED. CIR. JOURNAL 581 (2016) (detailing the rise in use of choice based conjoint analysis to estimate patent damages). *See, e.g.*, ConAgra Foods, Inc., 844 F.3d 1121(9th Cir. 2017) ("marketing researchers have used conjoint analysis since the early 1970's to determine the values consumers ascribe to specific attributes of multi-attribute products and to understand the features driving product preferences," holding that conjoint analysis is a reliable way to calculate class-wide damages); TV Interactive Data Corp. v. Sony Corp., 929 F. Supp. 2d 1006, 1022 & n.6 (N.D. Cal. 2013) (holding that choice based conjoint analysis is accepted in the relevant community and listing "a handful of cases to demonstrate that conjoint analysis is increasingly used in litigation"). *See also* Dzielak v. Whirlpool Corporation, Civ. No 2:12-0089 (D.N.J. 2017) at 11.

[10] Choice based conjoint is a specific form of conjoint analysis using a choice survey. For the seminal paper creating conjoint analysis *see* Paul Greene & V. Srinivasan, *Conjoint Analysis in Consumer Research: Issues and Outlook*, 5 J. OF CONS. RESEARCH 21 (1978); Paul Green, Douglass Carroll, and Stephen M. Goldberg, *A General Approach to Product Design Optimization via Conjoint Analysis*, J. MARKETING., (1981).

Choice Based Conjoint, originally derived from marketing research in business schools[11], seeks to estimate the value that consumers place on various features of a product. In patent infringement cases, the method estimates how much a consumer is willing to pay for the patented feature at issue. In false advertising cases, the method estimates how much a consumer is willing to pay for a product given its false claim. These estimates of willingness to pay for a feature then directly translate to the damage award an infringer or false advertiser must pay.[12]

To estimate these values, the method asks consumers to make choices between hypothetical products that vary on several features[13]. For example, a consumer might see three products in a CBC survey (say cell phones) that vary on several features (price, brand, color, service provider, etc.)

Product 1: Black Verizon Samsung phones at $400.
Product 2: White AT&T iPhone at $500.
Product 3: Black T-Mobile Android pones at $550.

The consumer will then choose which of the three products they prefer the most. She will do this several times with a different set of three products which systematically vary on their color, carrier, brand, and price. Then, using the choices of the consumer, statistical analysis can be used to determine how much a consumer is willing to pay for a cell phone given that it is made by Apple instead of Samsung or how much a black cell phone is worth in comparison to a white one.

The problem is that the method, although validated and used wisely in several non-legal contexts[14], is consistently misapplied by federal courts. Courts are

[11] For a full discussion of how conjoint analysis has develop and been applied in the business school context, *see* infra Section 2.

[12] Generally, the estimate of the willingness to pay for a patented feature is then multiplied by the number of products sold to get a total damage award. The same calculation applies in the false advertising context.

[13] We use the terms feature and attribute interchangeably throughout.

[14] The method has been used to value features of various product categories including but not limited to airplanes, furniture, cars, cell phones, computers, houses, etc. The list of articles using choice based conjoint analysis is vast and beyond the scope of this article the following list is just meant to be representative: Pinya Silavoi and Mark Speece, *The Importance of Packaging Attributes: A Conjoint Analysis Approach*, 41 EURO. J. OF MARKETING 11, (2007); Dick Wittink and Philippe Cattin, *Commercial uses of Conjoint Analysis: An Update*, 53 J. OF MARKETING (1989); Erik Olson, *It's Not Easy Being Green: The Effects of Attribute Tradeoffs of Green Product Preference and Choice*, 41 J. OF THE ACADEMY OF MARKETING SCIENCE 2, (2013).

incorrectly choosing which features to use in CBC studies. Products are made up of many features—some minor (not primary drivers of purchase decisions) and others major (primary drivers of purchase decisions). Choosing which features to include in a CBC study is a critical decision as omitting certain features can affect the values the method produces. All features of a product cannot simultaneously be included in a CBC study, however, because the number of combination of choices for the respondents grows and becomes cumbersome.[15]

As such, courts commonly reduce the set of features to be included in the survey. They routinely include only the minor patented (falsely advertised) features and mistakenly omit many of the major features. For example, to estimate the value of the patented rounded edges and app orientation of a smartphone, courts may omit major important features such as brand, color, size etc. of a smartphone.[16] Many federal courts design CBC surveys in the following way:

> Product 1: A smartphone with rectangle application orientation with rounded edges at $400.
>
> Product 2: A smartphone with square application orientation with sharp edges at $500.
>
> Product 3: A smartphone with no application orientation with rounded edges at $550.

This process of omitting major features produces an unrealistic survey. It creates the impression that products are only made up of relatively minor, patented (falsely advertised) features. When courts use this abridged design, the CBC methodology does not accurately value the patented features of a product. The omission of major features inflates the value of the included minor features, thereby inflating damage awards.

For example, a misapplied CBC study in the now famous *Apple v Samsung* case found that consumers were willing to pay $102 for a specific patented

[15] For a discussion of how too many attributes can negatively affect how consumers interact with a choice experiment *see* James Betterman, Mary Luce and John Payne, *Construction Consumer Choice Processes*, 9 J. OF CON. PSYCH. 2, (2008); Barbara Fasolo, Gary McClelland and Peter M Todd, *Escaping the Tyranny of Choice: When Fewer Attributes Make Choice Easier*, 7 MARKETING THEORY 1 (2007); Pablo Marshall and Eric Bradlow, *A Unified Approach to Conjoint Analysis Models*, 97 J. OF AMERICAN STATISTICAL ASSOC. 459 (2002).

[16] Both of these features are part of Apple's patent portfolio on their iPhone.

autocorrect feature when the full price of the smartphone was only $149, leading to an over $1 billion damage award. [17]

This Article intends to realign the CBC method with the spirit of damages: compensating parties for only the value of the patented (falsely advertised) features. This Article is in four parts. Part one lays out how damages are calculated in the patent infringement context and why they are important to the false advertising context. Part two explains the CBC method, including its history, traditional uses, and empirical design. Part three explains how the method is being used in both patent and false advertising lawsuits. In particular, part three discusses in detail how the method was applied in several representative cases and what the conclusions were. In part four we criticize the way the method has been applied and show the consequences of its misapplication. We do this by empirically showing through a novel experimental CBC design how omitting major features of a product inflates the value of the included minor features—thereby inflating damage awards. We conclude with how the method can be better applied to the question of patent and false advertising damages.

I. Patent and False Advertising Damages: A Primer

Estimating damages is critical for both patent infringement cases as well as class certification in false advertising cases. This section will first discuss how patent damages are apportioned including the various forms of patent damages. We focus specifically on design and utility patents that are part of multi-component products (e.g. the patent covers only some feature(s) of a product that is made up of many other non-infringed features). For example, a design or utility patent may cover some aspect of a cell phone (ex. texting software) but not cover other aspects of the phone (brand, color, price, size, etc.).

We will then discuss the importance of estimating damages in false advertising cases, particularly in the context of certifying a class. In this area we again focus on a product that is described by many features. For example, an orange juice box that makes many product-oriented claims (ex. 100%

[17] Apple Inc. v. Samsung Electronics Co., 920 F. Supp. 2d 1079, 1089 (N.D. Cal. 2013)., Expert Report of John. R. Hauser, Table 9 page 65. This is obviously a grossly exaggerated estimate of how much consumers are willing to pay for an autocorrect feature in part because of the omission of major features of a smartphone. Yet the court found the evidence compelling.

juice, all organic, Non-GMO, etc.). We do not intend this to be an exhaustive discussion of damages in both of these forms of lawsuits, but instead hope to give a brief background so that we can show and criticize how choice based conjoint methods have been applied in estimating such damages.

A. Patent Damages

Calculating patent damages for multi-component products is a critical part of any patent infringement lawsuit. In order to prove infringement, a plaintiff must 1) show that their patent was validly granted, and 2) that the patent was copied (infringed upon) by the defendant.[18] However, this alone does not guarantee a monetary payout and often does not get the plaintiffs case to a jury in the first place.[19] A plaintiff needs a theory and ultimately an estimate of the damages they faced due to the infringement.

In general, patent infringement damages can take two forms: the lost profits that the holder of the patent would have received had the infringer not used the patent and/or a reasonable royalty that the infringer would have paid the patent holder in a hypothetical negotiation.[20] For multi-component products, the damage award is further complicated. In this context, the courts require litigants to apportion damages with respect to the value of the patented component (e.g. a plaintiff only receives damages with respect to the value of the product that was patented and was infringed on, not with respect to the value of the full product.)[21]

[18] 35 U.S.C. Section 271 (a) which reads in part "whoever…sells any patented invention…during the term of the patent, infringes the patent." Effectively then, plaintiffs must prove that there was a patented invention and that the defendant used the patent in commerce.

[19] *See* Apple, Inc. v. Motorola, Inc supra note 7. In that case, Judge Posner objected to the introduction of damages by experts (under a *Daubert* motion) and held that there was no cognizable damage even though there was an infringement. Other cases have held similarly eBay Inc. v. MercExchange, L.L.C., 547 U.S. 388, 391-92 (2006); Lindermann Maschinenfabrik GmbH v. American Hoist & Derrick Co., 895 F.2d 1403 (Fed. Cir. 1990).

[20] *See* Sidak note 9 at 583. *See also* Aro Mfg. Co v. Convertible Top Replacement, Co., 377 U.S. 476, 507 (1964); Panduit Corp v. Stahlin Bros. Fibre Works, Inc., 575 F.2s 1152 (6th Cir. 1978). For a discussion of the characteristics courts take into consideration to evaluate a 'hypothetical negotiaton' for a reasonable royalty *see* Georgia-Pacific Corp. v. U.S. Playwood Corp., 318 F. Supp. 1116, 1120 (S.D.N.Y. 1970). For discussions of treatment of bargaining power in the estimation process *see* J. Gregory Sidak, *Bargaining Power and Patent Damages*, 19 STAN. TECH. L. REV. 1, 5 (2015).

[21] "[a] patentee…must…separate or apportion the defendant's profits and the patentee's damages between the patented feature and the unpatented features." (Garretson v. Clark, 111 U.S. 120, 121 (1884)). *See also* Sidak supra note 9 at 585; Ericsson, Inc. v. D-Link Sys., Inc., 773 F.3d 1201 (Fed. Cir. 2014).

This requirement for multi-component products creates a need for experts to estimate the value of the patented featured independent from the other features of the multi-component product. "In other words, the damages expert must employ a methodology that will enable him to disaggregate the profit that is 'property and legally attributable to the patented feature' from the profit that is attributable to the non-infringing feature of the multi-component product."[22]

A simple example will make this multi-component requirement clear. Take for example a pair of headphones. Assume that company X creates a new technology that molds the headphones into an oval design that more easily fits into an ear. Company X gets issued a design patent so that they are the only headphone manufacture that can employ this kind of oval design. Company Y (a competitor to company X) sees how great the design is and incorporates the design into their headphones. Company X then brings a suit for patent infringement. Assuming that they prove that they own a patent and that Company Y infringed on it, Company X must still show that the infringer caused some damage to the patent owner. Here, given that a pair of headphones is a multicomponent product (e.g. there are other important features of the headphone other than the oval design such as noise reduction, fidelity, etc.), Company X will have to apportion their lost profits or estimate a reasonably royalty *for just* the oval design—not the headphones as a whole.

In order to value the particular novel patented featured of the multi-component headphone product, experts would opine on what portion of the price paid for the headphones was due only to its oval design.[23] Alternatively, what is the consumer willing to pay for a pair of headphones with the oval design in comparison to the same pair of headphones without the oval design? This is the so called, willingness to pay (WTP) of the patented feature.[24] Ultimately, to effectively calculate damages in this context, the plaintiff has to introduce evidence that estimates the WTP of an oval design of headphones.

It is here in which economists, marketers, and other business academic scholars have been called into court. These experts have used various methodologies to estimate a WTP for a given patented feature of a multi-component product. The most common methodology is the subject of this paper—choice based conjoint analysis. Below we give more details on the method and how exactly the method can be used to estimate the WTP for a

[22] *Id*. At 585 quoting *Garreston*, 111 U.S. at 121.
[23] *Id*.
[24] Allenby supra note 9.

patented feature and thereby used to calculate total damages in infringement lawsuits.

B. False Advertising Damages

In addition to using choice based conjoint in patent damages. Plaintiffs have been looking to the same method to certify classes in false advertising and misleading labeling lawsuits.[25] Having a theory and estimation of class wide damages at the outset of a class action lawsuit is critical to getting over the hurdle of certification.[26] Rule 23 of the Federal Rules of Civil Procedure lays out the requirements for a class to be certified[27]. Most simply they are proving an adequate class definition[28], commonality[29], ascertainability[30], numerosity[31], typicality[32], adequacy,[33] and at least one of the requirements in rules 23(b).[34]

Although the requirement for showing harm is not explicitly mentioned in Rule 23, it can be easily read into the requirements for a class definition[35], commonality[36], and even Rule 23(b)(3).[37] Moreover, after *Comcast*, showing that class wide damages can be estimated if effectively a requirement to

[25] *See* In re: Dial Complete Marketing MDL Case (using choice based conjoint analysis to certify a class by showing that all consumers were hurt by Dial's false label claim) and *Briseno* (using choice based conjoint analysis to certify a class by showing that all consumers were hurt by ConAgra's false claim).

[26] *See* supra note 4.

[27] Fed. R. Civ. P. 23.

[28] Marcus v. BMW of N. Am., LLC, 687 F.3d 583 (3rd Cir. 2012); Young v. Nationwide *Mut. Ins. Co.*, 693 F. 3d 532 (6th Cir. 2012); Messner v. Northshore Univ. HealthSystem, 669 F.3d 802 (7th Cir. 2012).

[29] Wal-Mart Stores, Inc. v. Dukes, 564 U.S. 338 (2011).

[30] *Marcus,* 687 F. 3d 583; Hayes v. Wal-Mart Stores, Inc., 725 F. 3d 349 (3rd Cir. 2013).

[31] *Id*.

[32] *Id*.

[33] Amchem Products., Inc. v. Windsor, 521 U.S. 591 (1997).

[34] Rule 23(b) provides for the class to be easily identifiable as one of three types of class actions.

[35] A class action must not be so broadly defined as "to include a great number of members who some reason could not have been harmed by the defendant's allegedly unlawful conduct." (*Messner*, 669 F. 3d at 824-25). *See also* Edward F. Sherman, *Class Actions after the Class Action Fairness Act of 2005*, 80 TUL. L. REV. 1593, 1616 (2006).

[36] Commonality effectively requires that the members of a class faced the same injury. For a detailed discussion of heightened commonality standards *see* A. Benjamin Spencer, *Class Actions, Heightened Commonality, and Declining Access to Justice*, 93 B.U. L. REV. 441, 492 (2013).

[37] *See* Lilly v. Jamba Juice Co., no 13-cv-02998 (N.D. Cal. Sept. 18. 2014) (holding that a class was not certified because Rule 23(b)(3) was not satisfied when there was no showing of evidence of damages in the record).

getting certification.[38] Several class action lawsuits have failed at the certification stage because they have not shown a theory of how damages can be reliably estimated: *Rice v. Sunbeam Products*[39], *Dailey v. Groupon*[40], *Rahman v. Mott's LLP*[41], *Daniel F. v. Blue Shield of Cal.*[42], *Cabbat v Philip Morris USA Inc.*[43] among others. In some cases, estimating damages is difficult as the nature of injury is complicated. However, for many cases concerning false advertising including misleading packaging labels, the theoretical calculation of damage is quite simple.

In *Mott's* the court held that the damages of the mislabeled "No Sugar Added" would "likely involve demonstrating what portion of sale price was attributable to the value consumers placed on the 'No Sugar Added' statement." [44] This is often the case with misleading labeling class actions. To estimate damages, plaintiffs must show that the class members were "duped" into buying a product and would have paid less for the product had the packaging been truthfully labeled or alternatively, what percentage of consumers would have bought the correctly labeled product at its current price.

Take for example a soap company who labels its soap as killing 99.9% of germs.[45] It turns out, however, that the claim is only true for 85% of germs. A reasonable measure of damages here would be how much more consumers were willing to pay for the soap with the 99.9% label as opposed to the true label of 85%. When phrased in this way, the calculation is effectively a consumer's WTP for a soap that is labeled as killing 99.9% germs in

[38] Behrend, 133 S. Ct. 1426.

[39] No. 2:12-cv-07923 (C.D. Cal Feb. 14, 2014) denying certification of class action against Crock-Pots for making various misrepresentations about safety due to no introduction of expert evidence claiming a cognizable injury.

[40] No 11 C 05685, 2014 BL 237928 (N.D. Ill. Aug 17. 2014) denying certification of class action against Groupon for incorrectly calculating employee overtime wages due to no method of calculating class wide damages.

[41] 13-cv-03482 (N.D. Cal Dec 3, 2014) denying certification of class action against Mott's LLP for their misleading apple juice package labeled "No Sugar Added" because there was no readily available method introduced to calculate how much damage the label caused to consumers.

[42] 4:09 –cv-02037 (N.D. Cal. Aug. 11, 2014) denying certification of class action against Blue Shield of California for denial of health benefits because "plaintiffs have not offered any proof that damages can be calculated on a class wide basis."

[43] No. 10-00162 (D. Haw. Jan. 6, 2014) denying certification of class action against Phillip Morris for misleading consumers by using the term "light" in its description of cigarettes for not introducing sufficient methodology for calculating damages.

[44] Motts at 10.

[45] This is adapted from the In re Dial litigation as described further in detail infra Section 3.

comparison to the exact same soap that kills only 85% germs. This form of damage calculation looks extremely similar to the calculation of a multi-product patented feature. In fact, they are the same. In the patent context, plaintiffs attempt to apportion how much the patented feature contributes to the total price of a product. Similarly, in the class action context, plaintiffs attempt to apportion how much the mislabeled featured contributes to the total price of a product.

Given the similarity in questions, it is not surprising that the same method (choice based conjoint analysis) has been used in false advertising lawsuits in addition to patent infringement suits. It is actually the success of the method in the patent context that has allowed it to be recently readily utilized in the false advertising context.[46]

Both patent infringement and false advertising lawsuits need estimates of how much consumers are willing to pay for a small part of a product (often technological products in the patent context and consumer packaged goods in the false advertising context). Choice based conjoint analysis, developed by marketing scholars, has become the go to method for this estimation task. However, the method as we describe below has been inappropriately used. Therefore, experts using the method have often postulated drastically inflated WTP estimates which have led to inflated damage award in the billions of dollars.

II: A CRASH COURSE IN CHOICE BASED CONJOINT ANALYSIS

This section provides a brief overview of the accepted and preferred method for estimating the WTP of patented features of multi-component products and the WTP of misleading labels for consumer packaged goods. At the outset we should note that conjoint analysis is a well-accepted survey methodology that has been used in various business applications.[47] Thousands of articles

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[46] Note that one could simply ask consumers how much they are willing to pay for a product that kills 85% of germs instead of 99%. Although this seems easy to do, most scholars recognize that simply asking respondents how much they are willing to pay for a good is often an invalid method and scholars do not generally believe the results of these kinds of simple survey questions.

[47] The following is a non-exhaustive list of some articles that have used conjoint analysis to answer questions regarding preferences of various features of products in a business context: Gastón Ares, and Rosires Deliza. *Studying the Influence of Package Shape and Colour on Consumer Expectations of Milk Desserts Using Word Association and Conjoint Analysis*. FOOD QUALITY AND PREFERENCE, Eighth Pangborn Sensory Science Symposium, 21, no. 8 (December 1, 2010): 930–37; Rajeev Batra, Ramaswamy Venkatram, Alden Dana

have been written on the method that have innovated and provided new insights into the method and its uses.[48] We do not purport to summarize or do justice to the large academic repository of information on conjoint analysis. Instead, we simply seek to introduce legal scholars, judges, and practitioners to the very basics of the method here.

A. The Various Forms of Conjoint Analysis

Conjoint analysis can be best described as a form of survey methodology that seeks to determine what aspects (e.g. features) of a product consumers value and how much.[49] To field a conjoint survey, researchers choose various features of a product and create "profiles" for respondents to interact with. These profiles can be hypothetical configuration of products or real products that vary on a set of given features.

For example, if a researcher wanted to understand how consumers value various aspects of a computer, she may choose several features of computers to create hypothetical products: screen size, memory, price, brand, speed, etc. Once these features are chosen, the researcher then chooses the various levels of each feature to include in the study. For example, the research may be interested in studying three different screen sizes (15 inches, 19 inches, and

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L., Steenkamp Jan-Benedict E.M., and Ramachander S., *Effects of Brand Local and Nonlocal Origin on Consumer Attitudes in Developing Countries*, J. CONS. PSYCH. 9, no. 2 (January 25, 2008): 83–95; Paul E. Green, J. Douglas Carroll, and Stephen M. Goldberg, *A General Approach to Product Design Optimization via Conjoint Analysis*, J. OF MARKETING, 1981, 17–37; Anders Gustafsson, Andreas Herrmann, and Frank Huber, CONJOINT MEASUREMENT: METHODS AND APPLICATIONS (fourth edition), Springer Verlag (2007),: Berlin; Koutsimanis, Georgios, Kristin Getter, Bridget Behe, Janice Harte, and Eva Almenar. *Influences of Packaging Attributes on Consumer Purchase Decisions for Fresh Produce*, APPETITE 59, no. 2 (October 2012): 270–8.

[48] Again the following is a non-exhaustive list of articles that have innovated on the conjoint analysis method: Anocha Aribarg, Katherine A. Burson, and Richard P. Larrick. *Tipping the Scale: The Role of Discriminability in Conjoint Analysis*, J. OF MARKETING RESEARCH 54, no. 2 (2016) 279–92; Joel Huber, and John McCann, *The Impact of Inferential Beliefs on Product Evaluations*, J. OF MARKETING RESEARCH 19, no. 3 324–33 (1982); Joel Huber, *What We Have Learned from 20 Years of Conjoint Research: When to use Self-explicated, Graded Pairs, Full Profiles or Choice Experiments*, SAWTOOTH SOFTWARE RESEARCH PAPER SERIES (1997); Richard D. Johnson, and Irwin P. Levin, *More Than Meets the Eye: The Effect of Missing Information on Purchase Evaluations*, J. OF CONSUMER RESEARCH 12, no. 2 169–77 (1985).

[49] Specifically, the method calculates trade-offs between various features. But the modern application, relevant for this paper, seeks to answer how much a consumer values a given feature. The original method and its application was developed in the 1970s at The Wharton School, University of Pennsylvania, by Paul Green. *See* Green supra note 10.

20 inches), two different memory capacities (100GB, 250GB), three different prices ($400, $600, $700), and four brands (Apple, Dell, Gateway, Compaq). Using these features, and their respective levels, the researcher will create hypothetical products.

The ideal way to measure the values/tradeoffs of features is to run an experiment where several real products are introduced into the marketplace, that systematically manipulate prices of the products and the features at issue in a patent or false advertising case. A researcher would then simply be able to observe what sales and at what prices for various features. However, this is obviously costly and time consuming. Conjoint analysis is a survey methodology that attempts to simulate this ideal experiment with hypothetical products (and messages) shown to a sample of consumers.

Once these products are created, a researcher has three general options of how to structure the survey: ranking based conjoint, rating based conjoint, and a choice based conjoint.[50]

In a ranking based conjoint, a consumer will simply rank all the products that a researcher puts in front of them from 1 to n (n=the number of products in the survey). The task may look something like the following:

Please rank the following computers from 1-5 (1 being the most preferred and 5 being the least preferred).

Product	Price	Screen Size	Memory	Brand	Rank
A	$400	15 inches	100 GB	Apple	?
B	$700	19 inches	100 GB	Dell	?
C	$700	15 inches	200 GB	Dell	?
D	$600	20 inches	100 GB	Gateway	?
E	$400	20 inches	200 GB	Compaq	?

This information is then analyzed in a linear regression form with the rank as a dependent variable and the features (and their levels) as the independent variables. The regression would take the following form:

[50] Green supra note 10 at 57-61. *See also* David Reibstein, John E. G. Bateson, and William Boulding, *Conjoint Analysis Reliability: Empirical Findings*, 7 MARKETING SCIENCE no. 3 (1988) (comparing the reliabilities of the various forms of preference elicitation in conjoint analysis).

$$Y\ (Rank) = \alpha + \beta_1(Price) + \beta_2(Screen) + \beta_3(Memory) + \beta_4(Brand)$$

This allows the researcher to get estimates of the slopes (βs) of each of the features. These slopes represent the value (or utility) that the feature contributes to the overall value (or utility) of the product. However, ranking many products can be difficult for a consumer.[51] Ranking say 20 products from 1-20 is not an easy task as it is time consuming and burdensome for the respondent. In addition, ranking only gives ordinal information to a researcher, and hence, misses any ability to compare the relative magnitude levels. Moreover, it does not allow for ties (e.g. if a respondent is indifferent between two products).[52]

As such, a ratings based conjoint method can be used. In this method a consumer is given the same set of products but must rate them on a scale. The choice of what scale is often an important and consequential task. Rating say 20 products on a 1-100 scale will provide a lot of variability but may also be difficult for a respondent—the difference between a 50 and 51 is often a difficult task for a respondent to interpret. A smaller scale is often employed (say 1-10), which is easier for a respondent to use but then is more difficult to analyze due to limited variability.[53] In addition, respondents often do not use a scale uniformly. They have a tendency to give all attributes a 9 or a 10 (on a 10 point scale). This makes it more difficult to analyze the tradeoffs that respondents make between various features of products.

Again, once this data is collected, a linear regression is used with the rating as the dependent variable and the features as the independent variables is run. Similar to the rankings based conjoint, the estimates of the slopes represent the value that the consumer places on the given feature.

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[51] *See* Michael Pigone, Allison Brenner, Sarah Hawley, Stacey Sheridan, Carmen Lewis, and Daniel Jonas, *Conjoint Analysis Versus Rating and Rankings for Values Elicitation and Clarification in Colorectal Cancer Screening*, 27 JOURNAL OF GENERAL MEDICINE no. 1 (2012) (arguing that although choice based methods may be more realistic, both ranking and rating methods do produce similar results) ; Kevin Boyle, Thomas Holmes, Mario Teisl, and Brian Roe, *A Comparison of Conjoint Analysis Response Formats*, 83 AMERICAN JOURNAL OF AGRICULTURAL ECONOMICS no. 2 (2001) (finding that the various forms of conjoint do not always agree and ranking problematically does not allow for ties). *See also* Green supra note 10.

[52] Without ties, it is difficult for a researcher to fully understand the tradeoffs that a consumer would make in a real life setting.

[53] *See* Green and Srinivasan supra note 10 (finding that the choice of scaling of ratings in a conjoint design can affect its results.). *See also* Douglas Carroll, *Categorical Conjoint Measurement*, MEETING OF MATHEMATICAL PSYCHOLOGY, Ann Arbor, MI (1969).

Both rankings and ratings based conjoint studies are useful for certain applications. However, a choice based conjoint has become the most generally accepted method of employing conjoint analysis.[54] This is because choices represent a real purchasing task more realistically than both rankings and ratings.[55]

In a choice based conjoint, a researcher gives consumers choices between some subset of the hypothetical products. Instead of seeing say 20 products at one time, a researcher will show three or four products at a time and simply ask the consumer which product they prefer the most. The researcher analyzes these choices to estimate the value that consumers place on each of the features at issue. Rather than using linear regression for the choices, a multinomial logit regression is the preferred method of analyzing the data.[56]

Someone new to this task might ask why only a certain subset of features are included in the design of a conjoint study. This is because research has shown that respondents are overwhelmed with more than six or seven features.[57] If a conjoint design uses say 20 features, often respondents will ignore all the features except a few critical ones. This will frustrate the purpose of the task.

In response to this, researchers simply choose a subset of features to present to a respondent and then ask the respondent to "hold all features not present constant" across all of the presented products. This so called ceteris paribus language effectively tells the respondent that each of the products are exactly the same except for the differences in features that are presented.[58] This is a very common practice in conjoint design analysis and when used correctly does not create problematic results.

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[54] *See* Sidak supra note 9; Greene supra note 10 and Bradlow supra note 15.

[55] Terry Elrod, Jordan Louviere, and Krishnakumar Davey, *An Empirical Comparison of Ratings-Based and Choice-Based Conjoint Models*, 29 J. OF MARKETING RESEARCH no. 3 (1992) (although ratings based are valid measure, choice based methods often predict choices better than others). *See also* Cattin supra note 14.

[56] For a general discussion of the multinomial logit regression and how it is used *see* Peter Guadagni and John Little, *A Logit Model of Brand Choice Calibrated on Scanner Data*, 2 MARKETING SCIENCE no. 3 (1983). For a specific analysis of how a multinomial logit is used in choice based conjoint *see* Rick Andrews, Andrew Ainslie, Imran Currim, *An Empirical Comparison of Logit Choice Models with Discrete Versus Continuous Representations of Heterogeneity*, 29 J. OF MARKETING RESEARCH no. 3 (1992).

[57] *See* supra note 15.

[58] *See* Felix Eggers, John Hauser, and Matthew Selove, *Scale Matters: How Craft in Conjoint Analysis Affects Price and Positioning Strategie*s, 2017 (showing the various ways that ceteris paribus language can be used in a choice based conjoint and how that choice will affect the estimated willingness to pay of features).

However, as we argue and empirically show clearly below, using only a subset of minor features (features that do not drive the majority of the decision process) inflates the value of the included features. This is particularly problematic in patent and false advertising lawsuits as we delineate in Part Three below.

B. A Simple Example of Using Choice Based Conjoint Analysis

Almost all the conjoint analysis that is used in litigation (both for patent infringement and misleading labeling cases) uses choice based conjoint as the preferred method.[59] Again, this method creates the most realistic experience for a respondent, and hence, is thought to have the most external validity[60]. We show here a simple choice based conjoint example using the computer products from above.

Again assume that a researcher wants to understand how consumers value various features of computers. In particular, a researcher wants to understand how much are consumers are willing to pay for 1) a larger screen size, 2) more memory, and 3) an Apple computer versus a Dell. The design of each product will include price, screen size, memory and brand. Note that there are many other features that are likely important in deciding on what computer one will buy (sound output, graphics card, speed of processing, etc.). Since, these are not the focal point of the study, a researcher will omit these features and instead hold them constant amongst all products through the choice task.

Once the product features are decided upon, a researcher will create product profiles to compete with each other. The process of doing this ends up being incredibly important. A researcher will not randomly choose which products appear next to each other and what features each has. Instead, a researcher will use a balanced fractional factorial design.[61] In most basic terms, this

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[59] *See generally* Sidak supra note 9 591-598.

[60] External validity is concept in experimental settings that basically means how realistic is the study in comparison to the reality it is attempted to approximate. Studies can be very well designed and replicable over and over again, however, they may have little external validity, in which case they are likely not useful for the legal context.

[61] For an extended discussion of this kind of design *see* Keith Chrzan and Bryan Orme, *An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis*, SAWTOOTH SOFTWARE RESEARCH PAPER SERIES; Gustafsson supra note 47; Joel Steckel, Wayne DeSarbo and Vijay Mahajan, *On the Creation of Acceptable Conjoint Analysis Experimental Designs*, 22 DECISION SCIENCES no 2 (1991).

design allows a researcher to gain the most information about each feature utilizing the fewest choices while reducing respondent fatigue. A balanced design makes sure that the same level of feature (say $400) does not show up over and over again with another level of feature (say 200GB). If these two levels show up with each other too often, it becomes difficult for the researcher to disaggregate the value of each of these features.

Once a design is decided upon, the choices are presented to the consumer. Often, consumers are asked to choose on produce they prefer most amongst a set of 3-5 products, and a "none of the above" option.[62] This is what one choice in a choice based conjoint analysis might look like:

Please choose the computer that you prefer the most. If you prefer none, please choose "none." Note that all the computers are the same on features that are not presented here.

Product 1	
Price	$400
Screen	19 inches
Memory	200GB
Brand	Apple
O	

Product 2	
Price	$500
Screen	15 inches
Memory	150GB
Brand	Compaq
O	

Product 3	
Price	$500
Screen	20 inches
Memory	200 GB
Brand	Dell
O	

NONE OF THE ABOVE

The respondent would do this several times with several sets of three products.[63] Once a respondent goes through the choice tasks, their answers are analyzed using a multinomial regression. This regression estimates the value (utility) that the respondent places on each of the features and their levels. The estimates from this regression are called "part worths."[64] Part worths represent the utility that each feature adds to the total product. A small

[62] None options are important because in a realistic setting, sometimes consumers will prefer to not buy anything. Forcing them to make a decision when they otherwise would not will create problems in estimation. For a detailed discussion of the "none" option in choice based conjoint analysis *see* Rinus Haaijer, Wagner Kamakura, and Michel Wedel, *The 'No-Choice' Alternative in Conjoint Choice Experiments*, 43 INTERNATIONAL JOURNAL OF MARKET RESEARCH no. 1, (2001) (finding that not including a none option can results in much lower model and predictive fit and even biased estimates).

[63] The more choice tasks the respondent goes through, the better the results. Often 14-20 choices is standard.

[64] A part worth is basically a means of scaling and presenting the value of each level of a given feature in a conjoint study (Green supra note 10).

part worth means that that feature and its level only adds a little utility to the total product, while a large part worth means that the utility of the feature and its level account for a large percentage of the total utility of the product. Below is a sample of a choice based conjoint output:[65]

Attribute	Level	Part Worth (Utility)
Price	\$400	1.10
	\$500	0.13
	\$600	-1.50
Screen Size	15 inches	-1.00
	19 inches	0.52
	20 inches	1.36
Memory	250GB	-0.56
	500GB	0.62
Brand	Apple	1.69
	Compaq	-1.23
	Dell	1.01
	Gateway	0.06

This output allows the researcher to make at least three important insights. First, positive utility is better than negative utility. This means that a computer that is \$400 is more preferred to one that is \$600, which is intuitive. Second, the difference in the range of utilities for a given feature provides insight into how important that feature is relative to another feature. For example, the range of utility for "memory" is 1.18 (0.62-[-0.56]). While the range of utility for "brand" is 2.92 (1.69-[-1.23]). This means that the brand feature is more important to the respondent than memory as a feature. Third, the relative utility for a given level in comparison to price allows the researcher to compute a willingness to pay for a given feature. This is the most important insight for the legal context.

To calculate a willingness to pay, one first calculates a utility per dollar. To do this one takes the difference between the highest and lowest dollar amount (\$600-\$400=\$200). This dollar difference is associated with a difference of 2.6 utils (1.10-[-1.50]). Taking the ratio of the two (\$200/2.6=\$76/util) gives us an estimate of how much one utility point is worth in terms of dollars. We can then use this to calculate a willingness to pay. For example, the utility difference between a 19 inch computer screen and a 20 inch screen is 0.84

[65] These part worths are just for purposes of explaining how choice based conjoint results are interpreted. These are just fabricated part worths. Below in Part 4 we run an actual choice based conjoint and report estimated part worths based upon collected respondent data.

utils (1.36-0.52). We know that the consumer values one util at $76 so the willingness to pay for a 20 inch screen over a 19 inch screen is $76/util*0.84 utils = $63.84. This calculation can be done for whichever feature the researcher is interested in. In the patent context, as we show below, it is calculated between the infringed feature and the next best non-infringing alternative.

III: CBC APPLICATIONS IN PATENT AND FALSE ADVERTISING CASES

As described above, the choice based conjoint method (CBC) is an incredibly powerful and useful tool to answer questions about how much consumers value a feature of a multi-component product. As such, it has garnered much attention and use in litigation where valuing a feature of a product (or valuing the clam that a company makes on a product) is an important part of estimating damages. We described in detail several of the applications of choice based conjoint analysis in legal cases below. But first, we describe why the application in these contexts is problematic. In Part Four, we empirically show that the application of the method often creates biases in damage awards.

A. The Problem with CBC Analysis in Legal Cases

There are whole list of pitfalls that a designer of a CBC can fall into. Research in marketing scholarship has focused on various aspects of design that could bias results including potential inferences that consumers make with omitted variables[66], the presentation of non-symmetrical leveled features[67], missing levels of attributes[68], and realistic portrayal of features.[69] In addition there are

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[66] Richard D. Johnson , and Levin, Irwin P., *More than Meets the Eye: The Effect of Missing Information on Purchase Evaluations*, 12 J. OF CONS. RESEARCH, 169–77; (1985); Fredrik Carlsson, Mitesh Kataria, and Elina Lampi. *Dealing with Ignored Attributes in Choice Experiments on Valuation of Sweden's Environmental Quality Objectives*, 47 ENVIRONMENTAL AND RESOURCE ECONOMICS, no. 1 (2010); Islam, Towhidul, Jordan J. Louviere, and Paul F. Burke, *Modeling the Effects of Including/Excluding Attributes in Choice Experiments on Systematic and Random Components*, 24 INTERNATIONAL JOURNAL OF RESEARCH IN MARKETING, no. 4 (2007);

[67] Dick Wittink, Lakshman Krishnamurthi, and David Reibstein, *The effect of differences in numbers of attribute levels on conjoint results*, 1 MARKETING LETTERS 2 (1990); Rüdiger von Nitzsch, and Martin Weber, *The Effect of Attribute Ranges on Weights in Multiattribute Utility Measurements*, 39 MANAGEMENT SCIENCE, no. 8 (1993).

[68] Eric T. Bradlow , Hu, Ye , and Ho, Teck-Hua , *A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles*, 41 J. OF MARKETING RESEARCH, 369–81 (2004)

[69] Felix Eggers supra note 58.

many other generic issues associated with any kind of empirical survey that a court must be on the lookout for.[70]

Although application of CBC to legal cases implicate many of these problems, there is a specific unexplored problem that has plagued the use of CBC in litigation. As described above, presenting too many attributes to respondents is problematic because it creates too high of a burden for respondents. In effect, they will only look at a small subset of feature to make their decisions. As such, researchers often limit the number of features and ask respondents to hold all other features constant across the choices throughout the survey task.[71]

In the legal context, the features that are relevant for a given case (both patents and misleading labeling) are often very minor features. Major features that drive purchasing decisions are often not patented or lied about by companies. Features like price, brand, size, color are all incredibly important for consumers in choosing products AND are never really the subject of lawsuits. Instead, it is often relatively minor or unimportant features (e.g. design of edges, font type, orientation of icons, 99% safe versus 90% safe, etc.) that are the subject of lawsuits.

By “minor attributes” we mean those that are not the primary purchase drivers and may not even be considered in a normal purchase process. This is not to say that major features are the only features that consumers care about. Instead, we just note that major features are relatively more important than minor features. These minor features are still important for the companies at issue. They can implicate billions of dollars of damages as we describe further below. But, for the consumer, these features often play a very small (if any) role in the ultimate decision process. For example, the patented rounded edges of an iPhone are valuable to a consumer, but certainly not as valuable as the Apple brand, the price, the size, the color, the camera, etc.

To estimate the value of these minor features, litigation experts will simply omit more important major features in a CBC design and tell respondents to “hold those omitted features constant” across the choices throughout the choice task.

[70] This include issues like choosing a representative sample, making sure respondents understand the items in a survey, eliciting a reliable measurement of output, creating external validity etc. For a detailed list of these issues and insights into good survey design practice *see* Shari Diamond, “Reference Guide on Survey Research” in *Reference Manual on Scientific Evidence, Third Edition*, Federal Judicial Center (2011).

[71] *See generally* Part 2 above.

We argue, and empirical show below, that this routine strategic design choice has plagued expert damage reports and caused an inflation of damage awards in the billions of dollars. Omitting major features in order to estimate the willingness to pay of minor features biases the valuation of those included minor features upwards. Moreover, once this application of CBC is accepted by a few courts, it spreads through both the patent infringement and misleading labeling arena. The method, as it is currently being applied, is readily accepted in litigation.[72]

Until courts, lawyers, and ultimately experts recognize the problem associated with omitting major features so as to value the relevant minor features, damages will continue to be inflated, unjust, and inefficiently awarded.

Below we describe several patent infringement and misleading labeling cases where a CBC was used to value the relevant features. As we show, in all of these applications, the accepted approach was one that omitted major features from the design and included only minor features. In Section 4, we empirically show that this strategy leads to drastically inflated willingness to pay estimates and in turn recommended damage awards. In turn, many of the applications of choice based conjoint in the legal context have been biased and lead to inflated damage awards.

B. Sample CBCs Used in Patent Cases

Given that the crux of patent damages seeks to value what a patent is worth, a CBC that assists litigants in determining what a consumer is willing to pay for a patented feature is critical to any successful lawsuit. As such, the use of CBC in patent infringement cases has increased substantially. We summarize a few of these cases below spending most time on the recent *Apple v. Samsung* saga.

Apple v. Samsung (2011, 2012)

In 2011 and 2012, Apple sued Samsung alleging that Samsung had infringed on several Apple patents which protected aspects of iPhones and iPads. Specifically, Apple contested that Samsung had violated four design patents and three utility patents.[73] The case implicated several novel issues

[72] *See* supra note 7-8.
[73] Apple Inc. v. Samsung Electronics Co., 920 F. Supp. 2d 1079, 1089 (N.D. Cal. 2013).

concerning patent law, including how a multi-component product should be treated for patent damages purposes.[74] The procedural posture of each of the cases, their ultimate appeal to the Supreme Court of the United States, their remand, and their substantive issues[75] are all beyond the scope of this article.

Instead, here we just focus on the use of expert witness testimony in both cases and detail how experts used CBC to estimate the willingness to pay of the patented features. Estimating how much consumers were willing to pay for the various patented features provided Apple a guideline with which to claim that the willingness to pay per customer multiplied by the number of customers was an appropriate damage amount. This ended up being $1.049 billion even though Apple had asked for close to $2.5 billion.[76]

In both cases, Apple contracted a marketing expert to perform a choice based conjoint survey to estimate the wiliness to pay for each of the patented features. Several of the features at issues in both trials were intuitively very minor in the overall decision to buy an iPhone or an iPad. For example, in the 2011 trial, infringed patents included the rounded edges of the iPhone, the bezel on the iPad and iPhone, the orientation of the apps on the home screen, the rotation feature on the touch screen, and scrolling features.[77] In the 2011 case, Dr. Hauser, a marketing expert from MIT, was asked to design a CBC to estimate the willingness to pay of the relevant patented features. It was the data from that CBC that ultimately helped a jury find for the billion dollar judgment.

Dr. Hauser was also engaged to perform a CBC for the 2012 litigation. This litigation implicated patents like the Slide to Unlock feature for an iPad, Automatic Word Correction, Quick Links, and Missed Call Screen Management.[78] Intuitively, these features play a relatively minor role in the overall choice of which smartphone or tablet to buy. Most consumers do not

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[74] For an extensive discussion of the cases and how they were resolved *see* Elizabeth M. Gil, *Samsung v. Apple: Taking a Bite out of the Design Patent Article of Manufacture Controversy*, 25 U. MIAMI BUS. L. REV. 67, 88 (2017).

[75] For the Supreme Court's overturning of the lower court's jury award and subsequent remand *see generally* Samsung Electronics Co., Ltd et al v. Apple Inc. 580 U.S.__ (2016).

[76] *See* Nick Wingfield, "Jury Awards $1 Billion to Apple in Samsung Patent Case," *New York Times*, (Aug 23, 2012).

[77] Apple v Samsung (2013) supra note 68. The specific patent numbers were: United States Patent Nos. 7,469,381; 7,844,915; 7,864,163; D504,889; D593,087; D618,677; D604,305; and 504,889.

[78] The exact patents were '647 Patent, the '959 Patent, the '172 Patent, the '760 Patent, and the '414 Patent for smartphones and '721 Patent, the '647 Patent, the '959 Patent, the '172 Patent, and the '414 Patent for a tablet. Expert Report (Redacted) of John R. Hauser (August 11, 2013) in Case No. 12-cv-00630 at 5.

think about these features when deciding between an Apple smartphone and a Samsung smartphone. However, they do have some value to the consumer, and Dr. Hauser's job was to determine what that value was.

In designing his CBC, Dr. Hauser had to make several decisions on which features to include and which ones to exclude. Ultimately, he included all the minor patented features and only the following other major ones: screen size and price in the tablet design, and screen size, price, and camera in the smartphone design.[79]

Since there were so many minor patented features that Dr. Hauser had to include, in order to keep the CBC design reasonable, he decided to omit several important features and instead hold them constant throughout the choice tasks.[80] Nowhere in Dr. Hauser's design did brand, color, cell service provider, battery life, Bluetooth, and storage space (amongst others) show up. Instead, he focused mainly on using minor features. In fact, the features pages on Samsung's website "touted various entertainment related capabilities, such as Media Hub, the integrated IR blaster, the Smart Remote app, and the ability to use hands-free headsets, most of which were omitted by Professor Hauser in his analysis."[81]

We argue and show below that including only six features, of which the relevant patented four were extremely minor, at the expense of omitting various major features, caused Dr. Hauser's results to be unreliable.[82] Specifically, we show below that when one omits major features in a CBC choice task in order to include only minor features, the valuations of those minor features are biased upwards.

Interactive Corp. v. Sony Corp (2013)

A similar problem arose when Interactive Corporation alleged that Sony infringed on their auto-play feature patent when manufacturing the Sony

[79] Expert Report of John R. Hauser at 9.

[80] "Instructions were provided to focus respondents on making relative choices holding all other potential levels of feature categories of smartphones [tablet] constant." Id at 38. See *also generally* Expert Rebuttal Report (Redacted) of David Reibstein (Sept 13, 2013) in Case No. 12-cv-00630.

[81] Expert Rebuttal Report of David Reibstein at 125: "Professor Hauser's surveys did not, however, include numerous other features that Samsung prominently highlighted to consumers."

[82] *Id* at 117.

PlayStation.[83] Interactive hired Stanford professor Dr. V. Srinivasan, a marketing expert, to perform a CBC analysis to determine the willingness to pay of the auto-play feature on various Sony products (DVD Player, Blu-ray Player, and the PlayStation).[84] The auto-play feature allows consumers to continue to another disc in the console or player without having to manually select the next disc to play.

In designing his survey, Dr. Srinivasan took a twostep process. First, he had respondents "prioritize 18 attributes of each accused product to come up with a list of six attributes that have similar values as the auto play feature."[85] In effect, the design specifically chose attributes that were of equal value to consumers as the ostensibly unimportant (minor) auto play feature. The conjoint intentionally left out basically all major features including brand, controllers, processing speed, quality of picture, etc.

Second, Dr. Srinivasan fielded two CBCs where he used price, the auto play feature and six other similar minor attributes (3 in each of each conjoint) to create his product profiles. The court however, did not see any issue with this design and did not exclude the survey or the testimony.[86]

Oracle America, Inc. v Google Inc. (2010)

In another case, Oracle sued Google's Android operating system because they alleged that Google used seven patents related to Oracle's Java technology.[87] Once again, the plaintiff, Oracle, hired an expert witness to opine on the value of the patents for damages. Dr. Steven Shugan chose to run a choice based conjoint survey to value the patented smartphone features that Google allegedly infringed upon.

[83] TV Interactive Data Corp. v. Sony Corp., 929 F. Supp. 2d 1006 (N.D. Cal. 2013).

[84] *Id* at 1020.

[85] *Id*.

[86] *Id*. Specifically the court ruled that questions concerning Dr. Srinivasan's conjoint survey where questions for the jury. Although, query as to how a jury would be able to adequately determine the reliability of such a complicated quantitative method. But *see* Microsoft Corporation v. Motorola, Inc. et al, 2:10-cv-01823-JLR (W.D. Wash 2012), where expert Dr. R. Sukumar fielded a CBC survey on a similar product (the Xbox 360). In that CBC, Dr. Sukumar made a list of the most important features of the product and used those important features along with the patented features at issues to design his conjoint. This design where many major attributes are included is a much better practice that all experts should seek to emulate. Expert Report of Dr. R. Sukumar at 3-5.

[87] Oracle America, Inc. v. Google Inc., 3:2010cv03561 (N.D. Cal 2010).

In designing the survey, Dr. Shugan used only the following features: application multitasking, application startup time, availability of third-party applications, mobile operating system brand, price, screen size, and voice command capabilities.[88] Again, this CBC design omitted various important features that consumers might take into consideration when buying a smartphone including battery time, camera, touch screen capability, service provider, etc. In fact, for the court, this was egregious enough that Judge Alsup observed that "Dr. Shugan excluded from his analysis several important features unrelated to the patents in suit but include voice dialing, 'an arguably unimportant feature.'"[89] Judge Alsup held that the CBC "force[d] participants to focus on the patented functionality, warping what would have been their real-world considerations."[90]

This represents but another case where major features were omitted in order to estimate the value of relatively minor features. There have been other similar patent cases where a CBC was used to value patented features.[91]

C. Sample CBCs Used in False Advertising Cases

CBC surveys have also begun to be used in false advertising lawsuits to certify a class. Specifically, they have been used in contexts of consumer package goods. Often consumers when shopping in grocery stores, markets, or pharmacies, rely upon packaging and labels to make their ultimate decision. When labels are misleading or make false claims, it is likely that this will affect how consumers make decisions. This is at the heart of false advertising lawsuits.

The CBC method has been applied to estimate the damage to a consumer in the face of a misleading or false claim on the packaging of a good. The theory being that the consumer paid a premium for the product because they believed the false claim. To certify a class, plaintiffs must show that the class suffered a similar harm, amongst other things.[92] Showing that the consumer was

[88] Order Granting in Part and Denying in Part Google's *Daubert* Motion to Exclue Dr. Cockburn's Third Report at [ ] citing Shugan Report at 10, Oracle America, Inc. v. Google, Inc., 798 F. Supp. 2d 1111 (N.D. Cal 2011).

[89] Sidak supra note 9 at 605 quoting Judge Alsup's opinion in the Order Granting in Part and Denying in Part Google's *Daubert* motion.

[90] *Id*. At 15.

[91] *See e.g.* Fractus, S.A. v. Samsung Electronics Co., Ltd.., et al., 6:09-CV-203 (E.D. Texas 2013).

[92] For a list of requirements that must be proven to certify a class *see* supra section I(B).

willing to pay a premium due to the misleading or false claim at issue is a way to estimate damages in these kinds of lawsuits. As such a CBC has been the accepted method of estimating the willingness to pay for a given package claim.

The problem, as we will show below, is that once again, to do this, CBCs are omitting major features that drive a decision in context of packaged goods and only including those minor features. The minor features are often, if not always, the exact ones at issue. This strategy is likely causing the willingness to pay estimates of these minor features to be inflated upwards. It should be disconcerting also that several courts are accepting the results of these kinds of studies.

In re: Dial Complete Marketing (2017)

A CBC was used in a recent false advertising case against Dial Corporation.[93] Dial was accused of labeling their soap products with several misleading claims including that Dial Complete soap "Kills 99.9% Germs", that it is "#1 Doctor Recommended," and that it "Kills more germs than any other liquid hand soap."[94] In reality, plaintiffs alleged that the soap did not kill 99.9% of germs, but some smaller percentage and that it didn't necessarily kill more germs than other liquid soaps.[95]

Plaintiffs alleged damages equal to the premium that consumers paid in reliance on the truth of the Dial Complete Soap's claims. In estimating this premium for class certification purposes, plaintiffs relied upon an expert CBC study that attempted to calculate how much consumers were willing to pay for the soap conditional on them thinking that it killed 99.9% of germs.[96]

The expert, Mr. Boedeker, designed a choice based conjoint that purported to measure how much extra consumers were willing to pay for a soap that "Kills 99.9% of germs." Much like in the patent infringement context, this represents a need to value an ostensibly minor feature of a multi-component consumer product.

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[93] In re: Dial Complete Marketing MDL Case No. 11-md-2263-SM and Sales Practices Litigation, (D. N.H. 2017), Order granting certification.
[94] *Id*. At 3.
[95] *Id*.
[96] *Id*. at 4-7. In order to prove that the plaintiffs could satisfy the class wide damage calculation burden of Rule 23 they attempted to estimate damages using conjoint analysis.

In designing the CBC, Mr. Boedeker chose the following features of soap to include in his product profiles: "Kills 99.9% of Germs," "antibacterial," "foaming," and "moisturizing."[97] Finally he included price at eight different levels so he could measure the willingness to pay for liquid soap that had the label at issue.

Again, much like the CBC designs above, Mr. Boedeker's design did not include any major features that consumers use when purchasing soap (e.g. brand, size, dispenser type, scent, etc.). Instead, the design only included the relatively minor features at issue in the case.[98]. Yet, even though this CBC was clearly problematic, the court found that the method and its application were reliable, so much so that the court certified the class based upon the CBC analysis of Mr. Boedeker.[99]

Briseno v. ConAgra Foods Inc. (2015)

Unfortunately, the *Dial Corp*. CBC is only one of many problematic studies that have been used to certify classes in fase advertising lawsuits. In a similar case, ConAgra Foods Inc. was alleged to have used the phrase "100% Natural" on its cooking oil packaging, when in reality the product was made from genetically-modified organisms."[100]

The expert there, Elizabeth Howlett, performed a CBC to analyze the premium consumers placed on the "100% Natural" label. To do this, she first determined various interpretations that consumers may have had when reading the proposed language.[101] She came up with six interpretations, "the absence of artificial colors; the absences of artificial flavors; the absence of artificial preservatives; the absence of pesticides; the absence of GMOs; and

[97] *Id*. at 7.

[98] The minor aspect of the feature is the actual percentage of germs that are killed by the soap. The difference among 99%, 90% and 85% is minor when considering why somebody would purchase a hand soap in the first place.

[99] *Id*. at 30.

[100] In re ConAgra Foods, Inc. 90 F. Supp. 3d 919, (C.D. Cal. Feb. 23, 2015), Order Granting in Part and Denying in Part Plaintiff's Amended Motion for Class Certification.

[101] *Id*. at 948. *See also* Greg Allenby, Peter Rossi, Lisa Cameron, and Yikang Li, "Computer Damages in Product Mislabeling Cases: Plaintiffs' Mistaken Approach in Briseno v. ConAgra," Product Safety & Liability Reporter, 45 PSLR 208 (2017) (arguing that the CBC used in Briseno was problematic for other reasons not contemplated in this article).

the absences of artificial materials or chemicals used during processing."[102]

Second, Dr. Howlett simply used these six interpretations as "features" in her conjoint study. Nowhere in the study did brand, packaging, dispenser type, or even price show up. At a bare minimum, price should be included so that damages in the amount of dollars can be estimated. "However, a conjoint study can typically accommodate only six or seven product attributes. Hence, it is unclear how the proposed analysis could include other key product attributes, which must be included for the survey technique to work well." [103]

As such, the CBC that was used to certify damages against ConAgra. Dr. Howlett's conjoint, like several others, employed a strategy of omitting major features and instead focused only on minor ones, Of course, the court, relying upon several other previous courts who have certified classed based upon conjoint data, blessed Dr. Howlett's study and certified the class.[104]

Morales v. Kraft Foods Group, Inc. (2017)

In a case very similar to *Briseno*, Kraft Foods Group was sued for their use of the label "natural cheese" on their "Natural Cheese Fat Free Shredded Cheddar Cheese" packaging.[105] Again, like in *Briseno*, a choice based conjoint analysis was used to determine how much more consumers were willing to pay for the product with the "natural cheese" label.

Dr. Anand Bodapti was engaged to design and field a choice based conjoint that sought to estimate the willingness to pay of the "natural cheese" label. In designing his conjoint, Dr. Bodapti varied only one feature in his choices. He presented consumers with three types of products: competitors to Kraft Fat Free Shredded Cheese, Kraft shredded cheese, and the same Kraft cheese but without the "natural cheese" label.[106] In addition, he included price so that he could calculate the willingness to pay of the relatively minor feature of "natural cheese."

[102] *Id*. at 3.

[103] *Id*. at 4 (The conjoint in Briseno "will not provide a reliable estimate of consumer demand because it is focused entirely on attributes related to the 100% natural label and therefore leaves no room for consideration of primary factors in the consumer's purchasing decision, such as brand, price, packaging, etc.")

[104] In re ConAgra Foods, Inc. 90 F. Supp. 3d 919 at 1035.

[105] Morales v. Kraft Foods Group, Inc., 2017 WL 2598556, No. CV14-04387 (C.D. Cal. 2017).

[106] *Id.*

Again, Dr. Bodapti explicitly argued that he did not want to complicate the task for consumers by varying basically any important features in the cheese purchasing decision including the type of cheese, the cut of cheese, the packaging type, the brand, the close and keep fresh mechanism, etc.[107] Instead, Dr. Bopdati only included the relatively minor feature of a "natural cheese" label in his conjoint analysis. In effect, this conjoint only used one minor feature rather than several major ones—it seems particularly problematic in comparison to the other already problematic conjoint studies identified above.[108]

IV: THE MISAPPLICATION OF CBC IN LEGAL CASES AND ITS REALIGNMENT

A. The Problem with Omitting Major Features

As we have shown above, choice based conjoint analysis has been a large influence in estimating damages in both patent infringement and false advertising causes of action. Its application, however, has been problematic. As the number of problematic applications of CBC increase establishing precedent, the more likely courts will be to accept the method in its current form.

We shed light on how the current use of CBC to estimate the willingness to pay of features is biasing their estimated values upwards. The problem stems from the design of the conjoint. Because having more than six or seven features creates an undue burden on respondents, experts have limited the number of features they present in any conjoint. In doing this, they have to make choice on what features to include and which to omit.

Currently, the trend is to include the features at issue (mostly always very minor features) at the expense of omitting major features. When this happens, the estimated value (and, in turn, estimated damage awards) of the relevant included minor features are biased upwards.

We first give some insight into how we define minor versus major. A major feature (e.g. brand, price, color, size, battery life, etc.) is a feature that drives

[107] *Id*.

[108] In fact, when questioned on why he only varied one real feature in his conjoint, Bodapti testified that "having one attribute only is good for the conjoint analysis in the sense that it reduces cognitive overloading and thereby increases the fidelity of the decision making." *Id*.

the purchasing decision to some degree. This is not to say that major features are the only features that consumers care about. Instead, we just note that major features are relatively more important than minor features. Minor features (e.g. rounded edges, "100% natural" label, slide to unlock, icon orientation) in contrast are not principle drivers in the decision process. This is not to say that consumers do not have a preference for the given features (many do like and prefer the rounded edges of the iPhone), only that the feature is not something that a consumer would normally use in the process of buying a smart phone.[109]

Of course, what features are major and minor are not always clear. Often the importance of features lies on a spectrum with some very important and others very unimportant. We hope, and strongly believe, that most of the features described above in the applications of conjoint analysis are intuitively minor features relative to price, brand, size, etc. In addition, we strongly believe that the minor features we use in our study below are also intuitively much less important than the major features we explicitly omit.

There are three reasons that omitting major features biases the estimates of minor features upwards. First, the choice method itself forces respondents to make a choice amongst profiles. Often, the method creates a situation where the products presented to a consumer all match on major features. By this we mean, that the products have all the same major features. In those cases, the only difference among the products is the ostensibly minor feature(s). Therefore, the consumer is forced to make a choice wholly and solely based upon the minor feature…when in reality they would usually not base their decision solely on that feature.

Take a watch as an example. Most people when deciding among watches look at major features (price, brand, size, color, battery operated/automatic). It is reasonable to think that the engraving on the backside of a watch likely does not drive a decision in real life. However, take the following three choice based conjoint profiles:

[109] We note that there is heterogeneity in preferences. That is that some prefer minor features more than others. We can measure this heterogeneity, and do measure this, in our empirical study below. We also note, that even with heterogeneity, estimates of the value of minor features are biased upwards when major features are omitted.

Product 1	
Price	$100
Size	34mm
Brand	Omega
Engraving	Yes
O	

Product 2	
Price	$150
Screen	29mm
Memory	Swatch
Engraving	Yes
O	

Product 3	
Price	$100
Screen	34mm
Memory	Omega
Engraving	No
O	

Assume further, that a consumer prefers a 34mm Omega watch and holding all else constant wants a cheaper watch. The consumer then would NOT choose Product 2 as it is expensive, smaller, and the non-preferred brand. Between Product 1 and Product 3, the only difference is the presence of engraving. For this consumer then, if they prefer engraving they will choose Product 1 and if not, they will choose Product 2. In effect, the engraving (for this product choice) is driving the full decision making process. When in reality, no consumer really makes a decision based upon engraving. Instead, there are many other major features that are omitted here (color, battery operated/automatic, watch band type, watch band color, etc.) that could and should differentiate Product 1 and Product 3.

The statistical model however, will put all the weight of the decision a consumer makes in this choice set on the "engraving" feature. When this occurs a sufficient number of times, the value of the engraving feature will be inflated. The more major features that are omitted at the expense of including minor features, the higher the percentage of choices that will be completely driven by one of the minor included features.[110]

In this context, it is the choice aspect of the conjoint design that is problematic. If consumers could indicate not just that they preferred one product over another, but also *how much* they preferred that product, we would not see the same problem. As described above, using a scale of preference rather than just a choice would give researches more nuance in

[110] To quantitatively explore this we ran a CBC simulation where we used four features, each at two levels, two major features and two minor ones. When we analyzed the choice tasks, we found that in about 10% of the choice tasks, the minor features were completely driving the decision choice. The part worth estimates of this simulation showed inflated values for these minor features, although the major features were not inflated. As we added more major features to the simulation, we found that the number of choice tasks that were driven by the minor features went down substantially. In turn, the values of those features were depressed as well and approached previously defined known values. Because we simulated data, we avoided and consumer behavior biases (like focalism), yet still found an inflation of estimates of minor features. This only furthers our conviction. Choice based conjoint studies that omit major features cause many decisions in the survey to be driven solely by minor features, thereby inflating those features.

valuing preferences. However, having consumers rate products is more difficult than a choice based procedure and is less representative of a real purchasing decision.

Second, when presented with features that are minor (e.g., not really used in a real life decision context). A consumer will overweight those attributes because their attention will be drawn to them.[111] This phenomenon is called "focalism."[112] In effect, when a consumer is told about features that they otherwise would not consider in buying a product they tend to overweigh the importance of those features in a choice task.[113]

As one conjoint expert puts it:

Evaluation tasks intentionally force respondents to attend to attributes that they might otherwise not notice. In doing so, attention can elevate the importance of particular attributes to a level that is greater than would occur in the marketplace. For example, featuring the attribute 'surge protector' may make this attribute salient even though it may not be salient in actual choices…Simply mentioning an attribute increases its importance, raising the specter of attributes appearing important that otherwise would be ignored in the market choices.[114]

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[111]David A. Schkade, and Daniel Kahneman, *Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction*, PSYCH SCIENCE 9, no. 5 (1998): 340–46 (showing that citizens rate their cities higher on metrics that are easily observable and their attention is focused on those features that are presented to them on daily basis). *See also* Paul Dolan and Robert Metcalfe, '*Oops…I did it again': Repeated focusing effects in reports of happiness*, 31 *J. OF ECON. PSYCH.* 4 (2010) (finding that having respondents focus on certain features of a soccer game changed their forecasts of happiness of future soccer games); David M. Sanbonmatsu,, Frank R. Kardes, David C. Houghton, Edward A. Ho, and Steven S. Posavac, *Overestimating the Importance of the Given Information in Multiattribute Consumer Judgment*, 13 J. OF CONS. PSYCH. no. 3 (2003) (showing that consumer overvalue presented attributes leading to evaluations that are overly extreme).

[112] Timothy Wilson, Thalia Wheatley, Jonathan Meyers, Daniel Gilbert, and Danny Axsom, *Focalism: a source of durability bias in affective forecasting*, 78 J. OF PERSON. SOCIAL PSYCH. 5 (2000) (showing that people focus too much on presented events vs future events).

[113] Elizabeth Dunn, Timothy Wilson, and Daniel Gilbert, *Location, Location, Location: The Mispredicition of Satisfaction in Housing Lotteries*, 29 PERSON. SOCIAL PSYCH. BULL. 11, (2003) (finding that students rated their preferences of housing based upon highly variable physical features that were presented to them rather than non-presented more social features). *See also* Reibstein supra note 67 at 112-113.

[114] Joel Huber supra note 48, *What We have Learned from 20 Years of Conjoint Research,* at 244, 252.

For example, in the task above, many consumers will have never thought about whether they prefer a watch that has an engraving on the back. However, when they are presented with an option to have an engraving, they are more likely to pay attention to the feature in a way that they otherwise would not in a real choice task.

This a natural consequence of limiting features and having to value ostensibly minor features for patent infringement and misleading advertising cases. However, the phenomenon is made much worse when these minor features are included at the expense of major ones being omitted. In the misleading labeling examples above, most of the studies focused on showing respondents the "100% natural language" or some variant thereof. When it is the ONLY feature presented (or just one of a few), consumers will focus their attention on that feature and therefore will express a stronger preference for it than they otherwise would in a real life setting.

Third, many times features at issue in patent infringement cases are not readily known to consumers. They are simple not aware of the dynamics of the particular feature at issue or maybe that the feature even exists. For example, in *Apple v.* Samsung, one feature at issue was the form of the spell check that the iPhone employs. Very few, if any, customers really are aware of the particular spell check software on their phone. They know they have one and that is about all. Of course, when trying to value spell check, in a choice based conjoint that feature and its nuances must be included. In turn, consumers will seem to make decisions on features that they were not aware of before the survey started. This phenomenon is exacerbated when the majority of features presented in a conjoint are minor and less known. So not only is attention drawn to these features, but also consumers start utilizing these minor features in a way that they never would in a realistic setting because there was no awareness of them in the first place.[115]

[115] *See* Reibstein supra note 67, "Including features that customers are not currently aware of may not be a problem in every conjoint analysis. Such an approach is necessary with new products or products with new attributes in which survey respondents have not yet had real world experience in the marketplace. This deviation from reality is justified where respondents will be exposed to marketing or other communication such that at some point in the future the consumers are expected to be as informed about the product features as the survey respondents were when completing the exercises. In this case, however, the patented features are not unknown because they are new, but rather because they are minor features that the companies marketing the products and others evaluating the products consider relatively unimportant. As such, there is no expectation that the awareness of these features would change if the patented features were unavailable and design-around alternatives were offered instead. Simply put, consumers in the actual market can only react to information that they are aware of, and my review suggests that very few would be aware of the patented features." At 113.

These three effects (the forcing of a binary choice, focalism, and lack of awareness) lead the valuations of included minor features to be biased upwards when major features are omitted from a CBC. Little work has sought to show this phenomenon in both the legal and the marketing context. Below, we introduce a novel CBC experiment, field the experiment, and analyze it to empirically show that omitting major features causes the estimated willingness to pay of minor features to be biased upwards.

B. An Novel Empirical Example of Problematic CBC Analysis

<u>Overview of Study</u>

In the following study we attempt to show that when a CBC omits major features and includes mostly minor ones, the willingness to pay estimates of those minor features are biased upwards. We attempt to mirror as much as possible how CBCs are fielded in legal settings, with the hope to show that many of the damage awards that have relied upon CBC analysis by experts have been inflated for the included minor features.

In order to show this inflation, we have to experimentally field two randomized CBC studies and compare the results of each.[116] In one CBC we choose four major features and two ostensibly minor features (we discuss how we chose them below). In effect, we treat these two minor features like the features at issue in a patent infringement or misleading labeling context.

In our second CBC we include these same two minor features and omit three of the major ones replacing them with other minor features. This second CBC study represents exactly what many experts are testifying is appropriate science.

If omitting major features does not inflate the estimated willingness to pay of the included minor features, then both CBC studies should show similar estimates of the minor features that are the same across the studies.[117]

[116] As we describe further below, we use a between subjects design and randomly assign respondents to one of two CBC studies.

[117] Although these are two separate choice based conjoint studies with different respondents, we note that we randomize the assignment of each respondent to each CBC. Therefore, even though the people differ between the conjoint studies, and hence individual preferences might be different, the overall preferences when averaged out, should be same across both studies provided there is no bias. This is a standard assumption of experimental designs that seeks to find differences between two samples. If the differences are so large

However, what we find is that the estimated willingness to pay of the two minor features consistent across both of the studies is statistically significantly higher for the study in which the major attributes are omitted. We describe below in detail our stimuli, sample, procedure, model, and analysis/results.

Product Stimuli

For our experiment, we chose cars as our product of study. We did this for a variety of reasons. First, most consumers above the age of 18 have at least some experience with cars: buying a car, selling a car, driving a car, or at least riding in a car. In this way, many consumers are aware of cars and understand the various features associated with cars. This is an important factor in our study, because if we focused on products or features that consumers did not have experience with our results may not be valid.

Second, determining what consumers value in a car is a relatively easy task. There are several manufacture websites, blogs, used car searches, rental car websites that describe cars on a wide range of features. When one searches for car, or attempts to "build a car" on a website, the features that a consumer can choose from provide us some guidance in choosing major versus minor features.

Third, we use cars because judges in patent infringement cases have alluded to car decision making as an easy way to understand how a choice based conjoint study is designed and how it is used to estimate willingness to pay.[118]

Lastly, cars have been used extensively in other conjoint studies and as such have been validated as a useful product category to study the effects of conjoint design.[119]

(relative to the standard deviation), then we can conclude the differences are not by chance. This is exactly what we find below.

[118] *See* Apple, Inc. v. Samsung Elecs. Co., 735 F.3d 1352, 1368 (Fed. Cir. 2013) ("This is not to suggest that consumers' willingness to pay a nominal amount for an infringing feature will establish a causal nexus. For example, consumers' willingness to pay an additional $10 for an infringing cup holder in a $20,000 car does not demonstrate that the cup holder drives demand for the car. The question becomes one of degree, to be evaluated by the district court.)

[119] *See e.g.* Erik L Olson, *It's Not Easy Being Green: The Effects of Attribute Tradeoffs on Green Product Preference and Choice*, J. OF THE ACADEMY OF MARKETING SCIENCE 41, no. 2 (March 1, 2013): 171–84; Wann Yih Wu, Ying Kai Liao, and Anon Chatwuthikrai, *Applying Conjoint Analysis to Evaluate Consumer Preferences toward Subcompact Cars*,

Using publicly available information from autotrader.com, consumerreports.org; and J.D. Power and Associates rankings on cars, we chose four car features that seemed to be important (major features) in the marketplace.[120] These major features were the Price of a car, the Manufacture or Brand, the Miles per Gallon of a car, and the Vehicle Type. Each of these features had three levels.[121]

We also chose five attributes that seemed to be relatively unimportant (minor features) for consumers when making decisions. These minor features were: the number of Cup Holders, the location of the Gas Cap, the Clock Style, the Door Handle Type, and whether the car had Coin Slots.[122]

In choosing these minor features we attempted to choose features that we think do not play a large role in the decision to buy a car for most consumers.[123] Since many patented features and misleading labels at issue in litigation implicate minor features, we wanted our minor features to closely parallel legal cases. We contend that for the most part, that these minor features are objectively minor relative to the major features we choose. In addition, we attempted to choose features that would stand independent of

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EXPERT SYSTEMS WITH APPLICATIONS 41, no. 6 (2014): 2782–92.; Paul E. Green, and Venkat Srinivasan, *Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice*, J. OF MARKETING, 1990, 3–19.

[120] When visiting the J.D. Power and Associates ranking website the first thing consumers are presented with is categories of cars including various brands, types of cars, performance ratings, depreciation ratings, and customer service ratings. In addition, when visiting autotrader.com, the first set of search options include: price, vehicle type, year, brand, mileage, and fuel economy.

[121] For brands we chose Ford, Toyota, and Volkswagon. For MPG we chose 30, 40, and 50. For Price we chose $20K, $30K, and $40K. For Vehicle Type we chose a coupe (two door sports car), a sedan, and an SUV.

[122] For Cup Holders we chose three orientations: 1, 2 or 4 cup holders. Gas Cap represented which side of the car gas had to pumped into, we chose either the passenger side of the car or the driver side. Clock Style represented how the time was presented on the dashboard of the car, we chose three orientations: A digital clock, and analog clock, or a combined digital & analog clock. Handle Type represented how the door handle to each door was designed. There we chose a flat handle (similar to the Tesla door handle), a bottom handle which is a handle one must reach under to open, and a top handle which is one that can be grabbed from above the handle. Lastly we chose how many Coin Slots the car dashboard had: one or two. A Coin Slot was basically a device that allows a driver to hold a few quarters for easy access.

[123] There is of course heterogeneity to some degree in the sample we use. However, given that we are using a random experimental design, we think this heterogeneity does not affect our results.

each other.[124] Again, we suspect that most consumers have some preference on the minor features, yet *in reality* it is the major features that drive their decisions.

The Two CBC Studies

Once we decided on our stimuli, we had to design two separate conjoint studies. To do this we created what we define as an important conjoint (IMP) and subsequently an unimportant conjoint (UMP). The IMP conjoint represents a design that includes major features and a few minor ones of interest. The UMP conjoint represents a problematic design that omits several major features, and most includes minor features.

There are two minor features that are consistent across both the IMP conjoint and the UMP conjoint studies: the number of cup holders and the gas cap location. If we are correct in our criticism of the application of CBC to legal cases, then we should see the willingness to pay estimates for cup holders and gas cap location inflated in the UMP conjoint in comparison to their estimates in the IMP conjoint. This would mean that when major features are omitted from a conjoint design (as they are in many legal cases) in order to estimate relatively minor feature, those minor feature estimates are inflated.

Table 1 below shows the car features we use and their respective levels. It also shows which features we used for each of our conjoint studies. Appendix 1 reproduces the photos of each of the features we showed respondents so that respondents were informed about the various features presented.

[124] In effect, we did not want any of the features presented to interact with each other. This is an important point and we did perform a post-hoc test for interaction effects and did not find any statistically significant ones. Interaction effects are important because they can cause estimates to be biased upwards or downwards depending on the relationship among various features. For example, if consumers assume that a higher priced car has better cup holders than a cheaper priced car, this might influence the willingness to pay of cup holders in our study. In our studies, we specifically have chosen features that we have no prior reason to believe with suffer from interaction effects. If instead we had chosen a feature like leather seats, we might reasonably hypothesize that people would think a higher priced car or a more luxurious branded care would have better leather seats. This would make interpreting our results more difficult. For extended discussions on how conjoint analysis estimates are effected by interaction effects, *see generally* Green (1984) supra note 10; Bradlow & Marshall supra note 15; Eric T. Bradlow, Ye Hu , and Teck-Hua Ho, *A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles*, J. OF MARKETING RESEARCH, 41, 369–81 (2004); Joseph W. Alba, and Alan D.J. Cooke. *When Absence Begets Inference in Conjoint Analysis*, J. OF MARKETING RESEARCH 41, no. 4 , 382–87 (2004); Joel Huber, and John McCann, *The Impact of Inferential Beliefs on Product Evaluations*, J. OF MARKETING RESEARCH 19, no. 3 324–33, (2004).

Table 1: Attributes and Levels for CBC Experiment

Attribute	Levels	Important/ Unimportant	Conjoint
Price	$20K $30K $40K	Important	IMP & UMP
Brand	Ford Toyota Volkswagen	Important	IMP
Miles Per Gallon (MPG)	30 40 50	Important	IMP
Vehicle Type	Coupe Sedan SUV	Important	IMP
Cup Holders	One Two Four	Unimportant	IMP & UMP
Gas Cap Location	Passenger side Driver side	Unimportant	IMP & UMP
Clock Style	Analog; Digital Analog & Digital	Unimportant	UMP
Handle Type	Flat Bottom Top	Unimportant	UMP
Coin Slot	None One Two	Unimportant	UMP

<u>Sample</u>

We used Amazon Mechanical Turk to recruit respondents to field our CBC studies. Amazon Mechanical Turk is an online marketplace that allows businesses and individuals to quickly coordinate with human subjects to perform tasks. This includes fielding surveys and other empirical studies for many social scientists. Thousands of articles from disciplines including psychology, sociology, marketing, management, political science, and the law have utilized Mechanical Turk samples.[125] M Turk Respondents have been shown to be just as reliable as laboratory experiments in most cases. Using this online marketplace produces reliable and valid results and has become a norm in a social science.[126]

We recruited a sample 752 (n=396 for IMP Conjoint and n=356 for UMP Conjoint) respondents and paid each at a rate of $1/10 minutes of their time, which is the going rate for Mechanical Turk surveys.[127] Our sample was 58% male and had an average age of 35.

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[125] Thousands of articles have used Amazon Mechanical Turk and currently do. The following is non exhaustive list of articles that used the online marketplace specifically for conjoint studies: Thomas Stevens, Aaron Hoshide, Francis Drummond, *Willingness to pay for native pollination of blueberries: A conjoint analysi*s, 2 INTERNATIONAL JOURNAL OF AGRICULTURAL MARKETING no.4 (2015); Karoline Mortensen and Taylor Hughes, *Comparing Amazon's Mechanical Turk Platform to Conventional Data Collection Methods in the Health and Medical Research Literature*, 33 JOURNAL OF GENERAL INTERNAL MEDICINE 4 (2018); Kirk Bansak, Jens Hainmueller, Daniel J. Hopkins, Teppei Yamamoto, *The Number of Choice Tasks and Survey Satisficing in Conjoint Experiments*, 26 POLITICAL ANALYSIS no. 1 (2018); Cindy Wu, Scot Hultman, Paul Diegidio, Steven Hermiz, Roja Garimella, Trisha Crtuchfield, Clara Lee, *What Do Our Patients Truly Want? Conjoint Analysis of an Aesthetic Plastic Surgery Practice Using Internet Crowdsourcing*, 37 AESTHETIC SURGERY JOURNAL no.1 (2017); Yu Pu and Jens Grossklags, *Using Conjoint Analysis to Investigate the Value of Interdependent Privacy in Social App Adoption Scenarios*, ICIS (2015).

[126] *See* Michael Buhrmester, Tracy Kwang T., & Samuel Gosling, Amazon's mechanical Turk: A new source of inexpensive, yet high-quality, data?, PERSP. ON PSYCH. SCIENCE, 6(1), 3-5 (2011) (arguing that Amazon Mechanical Turk respondents are more diverse and the data obtained is just as reliable as more traditional methods).; Frank Bentley et al. *Comparing the Reliability of Amazon Mechanical Turk and Survey Monkey to Traditional Market Research Surveys,* CHI EXTENDED ABSTRACTS (2017) (discussing the reliability of traditional marketplace consumer research versus Amazon Mechanical Turk).

[127] Kotaro Hara, Abi Adams, Kristy Milland, Saiph Savage, Chris Callison-Burch, Jeffrey P. Bigham, *A Data-Driven Analysis of Workers' Earnings on Amazon Mechanical Turk*, Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (2018).

Design and Procedure

To design and field the conjoint studies we used Sawtooth Lighthouse Software.[128] Sawtooth is a widely recognized company that provides software for companies and researchers to use to build and field surveys. In particular, the company has developed somewhat of an expertise in choice based conjoint studies.[129] Many of the experts called on in patent infringement and misleading labeling cases have used and continue to use Sawtooth software to design, field, and analyze their conjoint studies.

In designing a conjoint, there are three major choices to make. First, what are the features and levels of those features for the product of study? We discussd those above. Second, how many product profiles will respondents see for each choice task? In both of our conjoint studies we used three car profiles and a none option (i.e. the respondents could choose one of the three products we presented, or indicate that they would choose none). Third, how many choices will respondents make? Too many choices leads to unreliable results because respondents get fatigued and stop caring.[130] Too few give a researcher too little information to draw nuanced insights. We decided upon giving respondents 14 choices to make, which was the recommended number in the software.

Once these decisions are made, Sawtooth Software creates a balanced fractional factorial design of choices. In doing this, the software calculates the best way to present products given the number of features and levels we designated so as to maximize the information gained from the least amount

[128] To see details on the software licensing and technical details, https://www.sawtoothsoftware.com/

[129] Sawtooth has become the main resource for experts in economic damages lawsuits. (*See* Proceedings of the Sawtooth Software Conference September 2016 accessed at https://www.sawtoothsoftware.com/download/techpap/2016Proceedings.pdf). In addition, Sawtooth publishes white papers on best practices in conjoint analysis with the assistance of marketing scholar, economists, statisticians, and business practitioners. For a sample of these whites papers *see e.g.* Eggers et al supra note 58; Martin Meissner, Harmen Oppewal, and Joel Huber, *How Many Options? Behavioral Responses to Two versus Five Alternatives per Choice*, SAWTOOTH CONFERENCE PROCEEDINGS (2016); Karen Buro and Jeremy Christman, *What a Difference Design Makes*, SAWTOOTH CONFERENCE PROCEEDINGS (2016); Jeroen Hardon and Marco Hoogergrugge, *Preferences Based Conjoint: Can it Be Used to Model Markets with Many Dozens of Products*, SAWTOOTH CONFERENCE PROCEEDINGS (2018).

[130] Richard Johnson and Bryan K. Orme, *How Many Questions Should You Ask in Choice-Based Conjoint Studies?*, SAWTOOTH SOFTWARE RESEARCH PAPER SERIES (1996) (finding that researchers can ask respondents to make up to 20 choices without seeing a degradation of results).

of choices.[131]

Once we recruited respondents via Amazon Mechanical Turk, they were randomly directed to one of two Sawooth designed CBCs—either the IMP conjoint or the UMP conjoint.

Instructions on the home page informed respondents that they would be making choices between several cars and that they should pay attention to the features and attributes presented to them. After this page, respondents going through the IMP conjoint study received detailed information about each of the six attributes and their levels that we chose in the IMP conjoint (Appendix 1 reproduces these images and descriptions). Those in the UMP conjoint study received detailed information about each of the six attribute and their levels that we chose for the UMP conjoint.

At the end of these information pages, respondents were told that they would be presented with 14 choices, each among 3 cars and 1 none option and they should choose the car they preferred the most. If they did not prefer any, they should choose the "none" option. Most importantly, they were told that "aside from the features presented in the study, all other features of each of the cars were the same"—standard instructions for a CBC study.

Once they started the choices each page presented three car profiles and one none option and asked respondents "If these were your only options for a car, which would you choose? All other features of the cars are the same."[132] Appendix 2 shows a sample of a choice set that a consumer might see in the IMP conjoint and in the UMP conjoint. We programmed the survey so that at any point, consumers could mouse over the particular feature and its level and see a photo of it. We did this because it helps respondents remember what each feature refers to and also increases the realistic aspect of the survey.[133]

The respondents then went through their assigned 14 choice sets. Finally, the respondents answered some demographic questions about their gender, age, ethnicity, and experience buying/driving cars.

[131] For a detailed discussion of fractional factorial design *see* Chrzan and Orme supra note 61. *See also* Steckel et al supra note 61.

[132] This so called ceteris paribus language (making sure that respondents know that all other non presented attributes are the same across profiles) is said to control for the omission of various major attributes. It is a staple of choice based conjoint design. *See generally* Eggers supra note 58. However, we show that even with this language, omitting features does bias the valuations of included minor features upwards.

[133] *See* Eggers et al supra note 58 (finding that using images as opposed to just text creates more realistic choice tasks and hence increases external validity).

Model

We analyzed our results from each of the conjoint studies separately with the intention of comparing the willingness to pay estimates of each of the two minor attributes we held constant across the studies. To estimate a willingness to pay, we first had to estimate part worth utilities[134] for each of the features/levels for both conjoint studies.

To estimate part worths utilities for our various features we assume that consumers make decisions with the following random utility model.[135]

$$U_{ik} = V_{ik} + \varepsilon_{ik}$$

Where U_{ik} is the utility derived by individual i for a given product k, V_{ik} is the deterministic part of the utility from profile k and ε_{ik} is the random component of i's utility for product k. The deterministic part of utility simply means the utility that the actual product gives to a consumer that is explainable. For example, in buying a smart phone, there is some level of utility that an iPhone gives to a consumer because of its features and functions. There is also however, a random component of utility that represents the unexplainable part of product's utility. Researchers can never understand "all facets of behavior germane to particular behavior outcomes of interest."[136] Therefore, we assume some randomness in the decision to buy a product.

We can further express V_{ik} as

[134] For a discussion of part worth utilities *see* supra section II(B).

[135] This model has been popularized in both conjoint studies as well as other choice modelling studies. It was originally popularized by Daniel McFadden and has been used subsequently in several empirical choice modeling contexts: Daniel McFadden, *Econometric Models of Probabilistic Choice*, in STRUCTURAL ANALYSIS OF DISCRETE DATA WITH ECONOMETRIC APPLICATIONS, Charles Manski and Daniel McFadden, eds (Cambridge, MA: MIT Press, 1981); George Baltas, *Random Utility Models in marketing Research: A Survey*, 51 J. OF BUS. RESEARCH no. 2 (2001); Greg Allenby and Peter Rossi, *Marketing Models of Consumer Heterogeneity*, 89 JOURNAL OF ECONOMETRICS no. 1-2 (1998); P.B. Seetharaman *Modeling Multiple Sources of State Dependence in Random Utility Models: A Distributed Lag Approach*, 23 MARKETING SCIENCE no. 2 (2004); Naresh Malhotra, *The Use of Linear Logit Models in Marketing Research*, 21 J. OF MARKETING RESEARCH 1 (1984).

[136] Jordan Louiviere, Deborah Street, Richard Carson, Andrew Ainslie, J.R. Deshazo, Trudy Cameron, David Hensher, Robert Kohn, Tony Marley, *Dissecting the Random Component of Utility*, 13 MARKETING LETTERS no. 3 (2002) at 181.

$$V_{ik} = \sum B_{jk} x_{jk}$$

Where V_{ik} is the value of the product k for individual i, x_{jk} is the value of the feature j for product k, and B_{jk} is the utility weight placed on feature j for product k for individual i. In simple terms, this means that we assume the observable utility that a consumer gets from a product is equal to the sum of the value of each of features that describe the product. The values of each feature (B_{jk}) then become the exact parameters we hope to estimate. These feature values are part worth utilities.[137]

Most modern conjoint analysis uses Hierarchical Bayes estimation to estimate these part worths and we follow suit.[138] Hierarchal Bayes allows for the estimation of part worths accounting for heterogeneity in consumer preferences.[139] To do this, we assume that the individual consumer part

[137] While this is a common model of choice, we note that there is a newer less used model called the surplus model. In the surplus model, rather than estimating part worths and then using those part worths to calculate a willingness to pay with respect to the price feature part worth, we could incorporate a willingness to pay within the model itself. This so-called surplus model takes the form: $S_{ij}\left(q_j, p(q_j)\right) = WTP_{ij}(q_j) - p(q_j) + \varepsilon_{ij}$ where $p(q_j)$ is the price associated with q_j unites of product j and $WTP_{ij}(q_j)$ represents the willingness to pay that consumer i associations with q_j unites of product j.

In this model on models directly the price premium (WTP) of an attribute. For an application of the surplus method to conjoint data *see* Iyengar Raghuram, Kamel Jedid, *A Conjoint Model of Quantity Discounts*, 21 MARKETING SCIENCE 2 (2012) and R. Wilson, NONLINEAR PRICING, Oxford University Press, New York (1993).

[138] Sample papers that have used Hierarchical Bayes in estimating part worths in a conjoint setting *see* Peter Rossi and Greg Allenby, *Bayesian Statistics in Marketing*, 22 MARKETING SCIENCE no. 3 (2003); Peter Lenk, Wayne DeSarbo, Paul Green, Martin Young, *Hierarchical Bayes Conjoint Analysis: Recover of Partworth Heterogeneity from Reduced Experimental Designs*, 15 MARKETING SCIENCE no. 2 (1996); Kenneth Train, *A Comparison of Hierarchical Bayes and Maximum Simulated Likelihood for Mixed Logit* (2001) (available in pdf form at https://eml.berkeley.edu/~train/compare.pdf); Bryan Orme and Gary Baker, *Comparing Hierarchical Bayes Draws and Randomized First choice for Conjoint Simulations*, Sawtooth Software Conference Proceedings (2000).

[139] Most simply, the statistical method allows us to estimate a unique part worth for each individual in our sample. If we did not use a Hierarchical Bayes estimation procedure, we would simply have to estimate one part worth for our whole sample. This of course would ignore the fact that people are different and that they have different preferences. So, the Hierarchal Bayes method allows us to use both the individual observations we have from our respondents and aggregate observations we have from all our respondents to calculate a unique part worth for each feature for each individual. For a more detailed technical discussion of the method, its assumptions, and implementation *see* Greg Allenby and Peter Rossi, *Hierarchical Bayes Models* in Handbook of Marketing Research: Uses, Misuses, and Future Advances, SAGE 2006; Jeffrey Rouder and Jun Lu, *An Introduction to Bayesian Hierarchical Models with an Application in the Theory of Signal Detection*, 12

worths follow a multivariate normal distribution of the following form:

$$B_i \sim N(\alpha, D)$$

Where B_i is a vector of utility part worths for individual i, α is a vector of means of the distribution of individual part worths and D is the matrix of variances and covariances of the distribution of part worths across individuals.

We also assume the following multinomial logit model[140] for predicting which profile in each task a consumer will choose:

$$P_{ik} = e^{V_{ik}} / \sum_{k=1}^{j} e^{V_{ik}}$$

Where P_{ik} is the probability of individual i choosing product k, and j represents the number of alternative products in the choice context.

We are then left with three parameters to estimate. B_i, α, and D. To estimate these parameters, we use a Markov Chain Monte Carlo[141] iterative process with conservative starting points equal to zero for all three parameters. We estimate one parameter while holding the two constant. We estimate another parameter using the values from previous estimates for the other two parameters. Finally, we estimate the third parameter using the values of the previously estimated parameters. We do this over several thousand iterations until our estimates converge. Our estimation converged after 20,000

PSYCHONOMIC BULLETIN & REVIEW no.4 (2005).

[140] A multinomial logit model is a common model that is used to analyze choice data. Generally if a research has collected data that has continuous dependent variable a linear regression can be used. However, when we have choice data (a binary dependent variable), a more accurate way to analyze it is to use a logit. The multinomial logit equation above most simply means that when consumers see the three product choices in our conjoint studies, the probability of a consumer choosing any one of the products over the others is equal to the ratio of utilities of the product to the sum of the utilities of the other products. For a more detailed technical discussion of the multinomial logit model *see* Guadagni and Little supra note 56; Raymond Adams, Mark Wilson, and Wen-chung Wang, *The Multidimensional Random Coefficients Multinomial Logit Model*, 21 APPLIED PSYCHOLOGICAL MEASUREMENT 1 (1997); Joffre Swait and Jordan Louviere, *The Role of Scale Parameter in the Estimation and Comparison of Multinomial Logit Models*, 30 J. OF MARKETING RESEARCH no. 3 (1993).

[141] For an introduction to the Markov Chain Monte Carlo iterative process *see* Don van Ravenzwaaij, Pete Cassey, and Scott Brown, *A simple introduction to Markov Chain Monte-Carlo Sampling*, 25 PSYCHONOMIC BULLETIN & REVIEW no. 1 (2018).

iterations and we averaged the utility part worths that were drawn from the iteration process.

Results

In Table 2 and Table 3 below we present the part worth utilities for each of the CBC studies we fielded. The part worth utilities we see here represent the value that the respective features and their levels add to the total value of the product. The higher the value of the part worth, the higher the utility of the feature, and therefore the more that feature figures into the decision making process.

Part worths are meant to be interpreted as changes in utility from one level of a feature to another. For example in the IMP conjoint, having a car that gets 40 MPG as opposed to 30 MPG increases the utility of product by 1.04 (0.15-[0.89]). Negative values should be interpreted as a less desired level of a feature. So, unsurprisingly, in both conjoint studies the utility is highest for the $20,000 feature level and lowest (most negative) for the $40,000 feature level. This simply means that consumers in both conjoint studies prefer a car that is cheaper to one that is more expensive.

We present two versions of estimated part worths. First, we present raw part worth utilities. These are simply the exact utilities that the estimation procedure produces. In addition, we present the median value of the distribution of part worths. The Hierarchical Bayes estimation calculates a unique part worth for each individual person. This is the benefit of using this estimation procedure as opposed to others which just give one global part worth value.

The difficulty is determining what to do with the distribution of part worths. In order to estimate a willingness to pay (as courts cases necessitate), one value has to be agreed upon. Using the mean is potentially problematic because it can easily be skewed by individual part worths that are extreme on either end of the spectrum. As such, the norm in a choice based conjoint that calculates a distribution of part worths is to use the median part worth to calculate a willingness to pay, and we follow suite.[142]

In the tables below, the grey cells represent the part worth values of the two

[142] *See* Rossi et al supra note 9 at 651 commenting on whether to use the mean or median part worth when a distribution of part worths is estimated. "However, there is no compelling reason to prefer the mean over any other scalar summary of the distribution of WTP. Some propose using a median value of WTP instead."

minor features that are held constant across both of the conjoint studies.

Table 2: IMP Conjoint Estimated Part Worths

Attribute	Level	Raw Part Worth (Median)	Zero Centered Part Worth (Median)
Price	$20,000 $30,000 $40,000	0.91 0.15 -1.14	55.53 8.35 -66.29
Miles Per Gallon	30 MPG 40 MPG 50 MPG	-0.89 0.15 0.72	-53.25 8.67 42.47
Car Type	Coupe Sedan SUV	-0.49 0.21 0.36	-33.87 12.70 22.50
Brand	Ford Volkswagen Toyota	-0.04 -0.27 0.28	-2.67 -16.21 16.67
Cup Holders	1 Cup Holder 2 Cup Holders 4 Cup Holders	-0.36 0.08 0.34	-21.60 4.28 19.91
Gas Cap Location	Passenger Side Driver Side	-0.07 0.07	-4.61 4.61

Table 3: UMP Conjoint Estimated Part Worths

Attribute	Level	Raw Part Worth (Median)	Zero Centered Part Worth (Median)
Price	$20,000 $30,000 $40,000	1.10 0.20 -1.53	74.74 12.33 -91.13
Cup Holders	1 Cup Holder 2 Cup Holders 4 Cup Holders	-0.74 0.07 0.68	-45.41 4.16 38.86
Gas Cap Location	Passenger Side Driver Side	-0.26 0.26	-15.49 15.49
Door Handle Type	Flat Handle Bottom Handle Top Handle	-0.57 0.20 0.39	-33.3 10.52 23.57
Coin Slot	None 1 Coin Slot 2 Coin Slots	-0.089 -0.091 0.19	-5.58 -5.47 10.92
Clock Style	Digital Analog Digital & Analog	0.25 -0.47 0.21	15.1 -27.91 12.16

If omitting major attributes (like we do in the UMP conjoint) does not bias the included minor features (cup holders and gas cap location), the estimated willingness to pay for each of the two features should be relatively the same across both conjoint studies. To determine this we calculate a willingness to pay (WTP) using the ratio of the price part worth and the feature part worths.

For the IMP conjoint, we calculate the dollar value for one utility point. To do this we take the difference in part worths between $20,000 and $40,000 (55.53-[-66.29])=121.82 and then divide this difference by the price difference ($20,000/121.82)=$164.17/util. Once we have a dollar per util value, we can simply multiply this by the feature levels that we are interested in. So if we want to know the value (i.e. the consumer willingness to pay) of 2 cup holders versus 1 cup holder, we simply multiply the $164.17/utils*(4.28-[-21.60]) utils= $4,248. Which represents how much consumers in our sample are willing to pay to have one more cup holder in their car.

We do the same procedure for the UMP conjoint in calculating the dollar per util ($20,000/(74.74-[-91.13])=$120.58/util. With this value, we can again calculate how much consumers in our sample are willing to pay for 1 more cup holder in our UMP conjoint.

Table 4 presents the willingness to pay for the minor features that we held constant across both the IMP and UMP conjoint studies.

Table 4: WTP Estimates from IMP/UMP Conjoint Studies

Attribute	**WTP IMP Conjoint**	**WTP UMP Conjoint**
1 to 2 Cup Holders	$ 4,248.89	$ 5,976.97
2 to 4 Cup Holders	$ 3,971.43	$ 5,187.19
1 to 4 Cup Holders	$ 6,814.97	$ 10,160.97
Passenger Side to Driver Side	$ 1,510.43	$ 3,735.46

What we notice here is that the WTP for cup holders and gas cap location is drastically (statistically significantly)[143] higher in the UMP conjoint than in

[143] We note that the WTP estimates in the UMP conjoint are all significantly higher (at

the IMP conjoint. The WTP for four versus one cup holder is 150% higher in the UMP conjoint than in the IMP conjoint. Even more shocking is that the WTP to move a gas cap from the passenger side to the drive side is more than 200% higher in the UMP conjoint. If only including minor features in a conjoint (as the UMP does) is not problematic as many experts seem to contend and courts seem to agree with, the differences in WTP for these minor features would not be so large.

Of course, this difference occurs precisely because the UMP conjoint omitted major features and only included a set of minor features. This is exactly what CBCs are doing in the legal context. By designing these conjoint studies to omit major features like brand, color, size, etc., court approved conjoint studies are inflating the WTP of those included features.

Our UMP conjoint represents exactly the forms of the CBCs that we describe above. Omitting major features in order to value many ostensibly minor features at the same time is inflating the value of these minor features. When the WTP is inflated, the damage awards are in turn also inflated as they rely directly upon the WTP calculation.

We note that our IMP conjoint also likely inflates the WTP for cup holders and gas cap location. We find it hard to believe that consumers would be willing to pay $1,500 to move the gas cap from one side of the car to another. We believe this is the case because so many other important features are still missing from both conjoint studies. No CBC can ever exactly mimic reality and produce completely valid results. However, the more major attributes that are included in a CBC, the more valid the WTP estimates become. As such, our WTP estimates from IMP conjoint likely matches reality more than the ones from the UMP conjoint.

In terms of litigation, we advise courts, litigants, and experts to heavily police the omission of major attributes in a CBC study. Although, any CBC that is employed is likely going to have some problems, the notion of omitting attributes is shockingly problematic. Our results show that estimates are almost double for some features when major features are omitted. In the patent context, this means that when Apple received over $1 billion in damages that resulted from a CBC that omitted numerous major features. Had an appropriate CBC been fielded damages might have been less than half of that amount.

5% confidence) than the WTP estimates in the IMP conjoint.

In addition, if the expert in *Briseno* had appropriately designed a CBC using major features and including the "100% natural" label at issue, the estimated WTP of the label might have been drastically smaller leading a court to deny the certification of the class. If there is such a small, insignificant price premium for the "100% natural" label, then a court is not likely to certify a full class. Therefore, we think this particular problem of omitting major features has caused several lawsuits to pass the Rule 23 hurdle, when the reality of the matter is that, the price premium estimates have been drastically inflated.

C. Realigning the Method

So, what can experts and courts do in the face of this potential bias? We seek to briefly introduce here three solutions here, but acknowledge that more work needs to be done to better understand how CBCs can be effectively used to measure a WTP of minor features.

First, we observe that the relative preferences of features can be validly estimated even in our UMP conjoint. Notice that in both the UMP and IMP conjoint studies, cup holders had a higher WTP and were more important in the decision making process than gas cap location.[144] The chosen features do not influence whether a given feature is more important than another feature. If a CBC is only being used to determine whether a feature is more important than another, its application in court cases is perfectly valid.[145] However, as soon as litigants seek to determine *how much more important* a feature is in terms of dollars, then biases of the sort we have identified here creep in.

Second, we recommend that when designing a CBC for patent infringement and misleading labeling applications, major features of the relevant products are always included. These cases generally implicate estimating damages for mostly minor features. In doing this, experts must focus on attempting to include as many major features as possible even if this means having to field several CBCs. For example, in *Apple v Samsung*, there were several minor

[144] To get a quick sense that cup holders are more important, we simply look at the range of part worths. The larger the range of part worths, the more important the feature. So for the IMP and the UMP conjoint studies, price was the most important conjoint, which makes sense with how consumers choose cars in marketplace.

[145] For example, if a researcher knows how much a certain patented feature is worth (either due to the fact that it is currently being licensed or another market drive valuation), a CBC can be used to determine if another patented feature is valued less or more than the feature with the known value. This would not allow for an exact WTP estimate of the feature at issue, but knowing whether it is valued more or less than an existing feature can provide a ceiling or a floor depending on the context.

patented features that Apple claimed Samsung infringed. The CBC attempted to value all of these features in one study. To this do of course, given that there can only be so many features presented to consumers, the expert had to omit major features.

Instead, a better method (albeit more expensive) would be to have run a different CBC for each of the patented features including only one minor feature at a time. In this way, each CBC could have used the major features of a smartphone and one minor patented feature. This would have likely depressed the estimated values of the patented features to more realistic levels and, in turn, the actual damage amounts.

Third, above we discussed two other forms of conjoint analysis: ranking and ratings based. We note that when analyzing choice versus ranking or ratings, there is less information. A CBC only tells a researcher that a consumer prefers one product over another. Ratings however, inform the research exactly *how much* a consumer prefers one product over another. Often, when it comes to minor features, consumers do have a preference but a small one. For example, consumers do prefer a driver side gas cap over a passenger side one. With only a choice based conjoint analysis, this is all the information a researcher obtains. Therefore, it is more difficult to estimate how much more a consumer prefers a driver side gas cap versus a passenger side one. With a ratings based conjoint study, a consumer tells the researcher exactly how much they prefer a car with a different gas cap location. This increase in information allows for a more accurate estimate of WTP.

As such, we recommend that conjoint studies seek to revert back to ratings based or rankings based preference elicitation. This is particularly important for estimating the value of relatively minor features because consumers often have such small preferences for these features relative to ones that are more likely to drive the purchasing decision.

CONCLUSION

We have sought to do two main things in this article. First, we hope to unpack the black box of choice based conjoint analysis for legal practitioners as it is an increasingly common method to estimate patent infringement and misleading labeling damages. In doing this, we have highlighted a common problematic practice in the design of CBCs. Experts in the face of attempting to value minor features are omitting major ones when designing a CBC.

Second, we empirically showed through two experimental CBC studies that this process of omitting major features is causing the estimates of the WTP of minor features to be inflated. When calculating the WTP of minor features, our UMP conjoint inflated values. This of course, leads to higher, inefficient damage awards that do not represent the reality of marketplace.

We hope that this article sparks more research into how conjoint analysis is being used, and abused, in litigation. Ultimately, we hope that courts can act as policing mechanisms to make sure that CBCs are not being used to drastically inflate damage awards leading to unfair, unrealistic, and inefficient judgments.

Appendix 1: Car Features and their descriptions

The sixth feature you will consider the clock of a potential car. The following types of clocks will be used:

Analog:

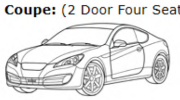
Digital:

Analog and Digital:

Back Next

The third feature you will consider is the type of potential car. The following three types will be used:

Coupe: (2 Door Four Seater)



Sedan: (4 Door Four Seater)

SUV: (Sports Utility Vehicle)

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The first feature you will consider is the brand of the potential car. The following three brands will be used.

Ford-An American manufacturer:

Toyota-A Japanese manufacturer:

Volkswagen-A German manufacturer:

Back Next

The fourth feature you will consider is the number of coin slots in a potential car. The following three options will be used:

No Coin Slot

One Coin Slot:

Two Coin Slots:

Back Next

The third feature you will consider is the door handle style of a potential car. The following three types will be used:

Flat Handle:

Bottom Handle:

Top Handle:

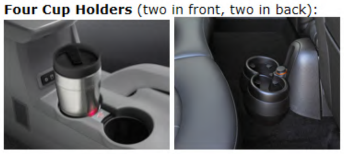
Back Next

The fifth feature you will consider is the number of cup holders in a potential car. The following number of cup holders will be used:

One Cup Holder:

Two Cup Holders:

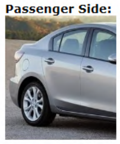
Four Cup Holders (two in front, two in back):



Back Next

The first feature you will consider is the location of the gas cap on the car. The following two orientations will be used:

Passenger Side:



Driver Side:

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Appendix 2: Sample IMP & UMP Conjoint Choice Tasks

IMP Conjoint:

If these were your only options for a car, which would you choose? All other features of the cars are the same.

(1 of 14)

Miles Per Gallon (MPG)	**30 MPG**	**40 MPG**	**50 MPG**
Gas Cap Location	**Passenger Side**	**Driver Side**	**Driver Side**
Car Type	**Sedan**	**SUV**	**Coupe**
Brand	**Ford**	**Volkswagen**	**Toyota**
Price	**$30,000**	**$20,000**	**$40,000**
Cup Holders	**2 Cup Holders**	**4 Cup Holders**	**4 Cup Holders**
	Select	Select	Select

NONE: I wouldn't choose any of these.

Select

UMP Conjoint:

If these were your only options, which would you choose? All other features of the cars are the same.

(1 of 14)

Price	**$30,000**	**$40,000**	**$40,000**
Cup Holders	**2 Cup Holders**	**1 Cup Holder**	**1 Cup Holder**
Door Handle Type	**Flat Handle**	**Top Handle**	**Bottom Handle**
Coin Slot	**No Coin Slot**	**No Coin Slot**	**No Coin Slot**
Gas Cap Location	**Passenger Side**	**Driver Side**	**Passenger Side**
Clock Style	**Digital and Analog**	**Digital and Analog**	**Digital**
	Select	Select	Select

NONE: I wouldn't choose any of these.

Select

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